Three Essays on Empirical Banking

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The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

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The Chairman of the Doctoral Board: Prof. Dr. Steven Ongena

To Heike, Noel, and Emilie

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Part I

Dissertation Overview

Dissertation Overview

The recent financial turmoil that began in late 2007 pinned the starting point of the worst financial crisis for decades. A new wave of bank runs shocked many modern and developed financial systems around the world. Big banks had to be rescued by their governments, which in turn began to stumble over large amounts of outstanding debt. Central banks in the U.S., in Great Britain, and particularly in the Eurozone area reacted decisively and flooded financial markets with cheap and long-term liquidity. The sovereign debt crisis in peripheral European countries to date challenges the survival of the European monetary system.

Understanding the determinants of financial crises in general as well as tackling the current crisis has become an important strand of economic research. While bank runs have long been thought to be a relic of the early 20th century, they reemerged in new clothing. In modern-day bank runs, we do not necessarily see long queues of depositors lining up in front of bank branches, eager to withdraw their deposits. Instead, it is large institutional wholesale investors that withdraw short-term deposits, refuse to roll over short-term debt or draw down on credit-lines. The threat of institutional bank runs makes studying system stability in a world of highly levered and short-term financed financial institutions indispensable.

The first chapter of this thesis, *Should I Stay or Should I Go? An Experimental Study of Banking Crises,* covers an empirical investigation of a theoretical bank run model. Since micro-level data about investors that are deciding whether they want to withdraw their funds early or leave it invested for longer is almost inexistent, I implement a controlled experiment similar to Klos and Sträter (2013) to measure the effect various treatments would have on withdrawal behavior. The experiment bases on the model of Diamond and Dybvig (1983) using an application of the global games approach by Goldstein and Pauzner (2005). I investigate the effects of priming subjects with a financial boom or bust scenario before they play a bank run game to study the effect of a mentally salient financial boom or bust, increased background fear and changed risk aversion. Furthermore, I also test the effect of level-k thinking, i.e., a measure to what extent subjects generate beliefs about other subjects' beliefs and further higher order beliefs. Finally, I change a parameter in the bank run game that determines the accuracy of the information that depositors receive before they decide when to withdraw their investment.

My results suggest that subjects primed with a bust treatment have an increased probability of withdrawing their deposit early. This could lead to a self-reinforcing feedback loop. Furthermore, higher orders of level-k thinking, as well as lower accuracy of private information, also increase the likelihood of bank runs. However, I do not find direct evidence that individual risk aversion or the emotion of fear impact system stability.

In the second chapter, *Which Swiss Gnomes Attract Money? Efficiency and Reputation as Performance Drivers of Wealth Management Banks*, which is a joint project with Urs W. Birchler, Michael R. Reichenecker, and Alexander F. Wagner, we study the effects that "skill" or bad media coverage have on the performance of Swiss private banks. The financial sector as a whole and the wealth management segment, in particular, are substantial contributing factors to GDP in Switzerland. Swiss banks have a long and successful tradition in managing assets for wealthy individuals. Especially in turbulent times, both economically and politically, Switzerland profited from its reputation as a financially "safe haven" and attracted large amounts of assets of foreign origin. Yet, a part of the attraction of Switzerland as a domicile for cross-border wealth may also be attributed to the Swiss banking secrecy combined with fraudulent business practices of Swiss banks. Many banks managed cross-border assets that were deposited in Switzerland because of tax evasion reasons. In recent years, international pressure against the Swiss banking secrecy increased; be it through theft of bank's client data, tax evasion scandals, or the introduction of the so-called automatic exchange of information that informs fiscal authorities of foreign countries about the bank accounts of its citizens in Switzerland.

In our paper, we first establish a measure of the unobservable "skill" of wealth management banks. We identify relatively skilled banks by using a regression model that explains cost-efficiency measured as the cost-income ratio. Banks that are more cost-efficient than predicted by their observable input factors are deemed to be more skilled. Second, we combine this skill variable with a measure of reputation changes to predict the performance in attracting net new money. For this purpose, we use a unique hand-picked panel data set of 98 private banks in Switzerland and Liechtenstein for the period 2002-2014 and measure reputation changes by generating an indicator variable for bad media coverage of individual banks in any given year.

We find that relatively cost-efficient banks perform significantly better in attracting net new money. Furthermore, we find that negative media coverage in one year sharply diminishes the ability to attract new funds in the coming year. This finding is particularly strong for small banks. The estimated present value of lost profits accounts to 3.35 (0.73) times the median annual net profit of small (large) banks. Strikingly, we do not find evidence that investment performance for clients has any explanatory power when attracting new funds. In sum, these results underscore the importance of trust in money management.

The third and final chapter, *The ECB's Three-Year Bank-Refinancing Operations and Eurozone Bank Equity* (joint work with Jiri Woschitz), investigates the impact of the European Central Bank's intervention on the Eurozone interbank market at the height of the European debt crisis in December 2011. At the time, banks faced a dry interbank market due to a loss of confidence. This impaired a smooth transmission of conventional monetary policy, such as lowering key interest rates, to the real economy. Since the looming threat of a credit crunch became ever more apparent, the ECB reacted to this adverse market condition with the announcement of two extraordinary three-year Longer-Term Refinancing Operations (LTROs). These are supplementary repo transactions that entitle banks in the Eurosystem to take up unlimited amounts of liquidity at a fixed rate for three years in exchange for eligible collateral. The demand by banks was extraordinarily high. In the two cash settlements, a total of 800 banks took up over EUR 1,018 billion in liquidity (in standard LTRO transactions roughly 100 to 300 banks bid for aggregate amounts between EUR 15 and 70 billion).

We claim that both the announcement of the transactions as well as the size of the first cash settlement represent unexpected large-sized shocks to the financial markets. To measure the effect of these shocks, we employ an event study methodology and assess the impact of liquidity operations on banks' equity prices. We estimate abnormal returns for 89 listed Eurozone banks across 12 different countries using a standard market model as described by MacKinlay (1997).

The results show that particularly banks in peripheral Eurozone countries show high positive abnormal returns during the announcement and the first cash settlement period. Furthermore, abnormal returns are highest in countries where liquidity uptake in the three-year LTRO transactions was high. This finding is in line with the argument that the three-year liquidity operations served as an indirect bailout for banks in financially weaker countries (Nyborg, 2017).

In sum, this dissertation contributes to a better understanding of the determinants of banking crises and attempts to decrease the gap between the theoretical predictions in global games theory and observed behavior in reality. Furthermore, it provides insight over efficiency and performance measures in private banking and emphasizes the value of trust in wealth management. Finally, it shows the impact of the hitherto largest unconventional repo transaction ever conducted by the ECB on bank equity prices in the Eurozone.

The structure of the dissertation is as follows. The three research articles are found as Chapters 1, 2, and 3 in Part II, for which Part III contains the Appendices. Part IV provides the bibliography, and Part V presents my curriculum vitae.

Part II

Research Articles

1 Should I Stay or Should I Go? An Experimental Study of Banking Crises

1.1 Introduction

The breakdown of Northern Rock, Bear Stearns, and Lehman Brothers are prominent examples of how financial institutions that rely heavily on short-term liquidity may quickly turn insolvent when investors decide to withdraw short-term deposits, neglect to roll over short-term debt or draw down on credit-lines. Many banks that used market refinancing and operated with high leverage using short-term debt experienced near-collapses in the banking crisis that started in late 2007. A critical aspect of this banking crisis is that bank runs were not necessarily started by retail customers but rather by institutional wholesale investors (Cornett et al., 2011; Gorton and Metrick, 2012; Ippolito et al., 2016).[1] The initial mortgage and liquidity crisis led to a credit crunch, an erosion of capital and eventually amplified into a global financial crisis (Brunnermeier, 2009). Many governments had to bail out their largest financial institutions using vast amounts of tax money, thereby, in turn, exposing themselves to solvency risks. The recent crisis has thus put a renewed focus on the regulation of liquidity as well as the term-structure of both the asset and financing side of banks specifically and financial institutions at large.

In this paper, I experimentally study how large and sophisticated wholesale investors coordinate on withdrawal decisions and potentially create banking crises. Specifically, I investigate the impact of priming subjects with a financial boom or bust scenario, measure the effect of higher order beliefs, and test whether less accurate private signals increase the likelihood of crises. The experiment used in this thesis is a classroom experiment based on Klos and Sträter (2013) that applies a global games approach by Goldstein and Pauzner (2005) on the model of Diamond and Dybvig (1983) (henceforth, D&D). While game theoretical models have clear predictions about behavior of market participants, empirical evidence using micro-data on institutional investors is still almost nonexistent.[2]

[1]Examples of such "institutional runs" on financial institutions were Northern Rock (Sep 2007), Bear Stearns (Mar 2008), Lehman Brothers, and Washington Mutual (both Sep 2008). For further analyses of institutional bank runs during the financial crisis, see Ivashina and Scharfstein (2010).

[2]Iyer and Puri (2016) is a notable exception. They study contagion and network effects on the withdrawal behavior of bank customers in a unique natural experiment for a bank in India that faced a bank run after the collapse of a neighboring bank.

Controlled experiments offer a simple way to test theoretical models and ceteris paribus changes of input parameters. I find that priming subjects with a bust scenario negatively affects system stability, individuals that generate higher order beliefs are more likely to lose trust in vis-a-vis other depositors, and noisier signals decrease system stability.

A bank generates liquid claims on illiquid assets (Goldstein and Pauzner, 2005). In doing so, a bank enables liquidity risk-sharing among different agents: impatient investors have the opportunity to withdraw deposits early, if needed, while patient agents benefit from profitable long-term investment and late withdrawal (Bryant, 1980; Diamond and Dybvig, 1983). Whenever a bank has sufficiently many agents (depositors) engaging in a demand deposit contract, the idiosyncratic liquidity shocks of individual agents can be eradicated and we achieve an equilibrium that Pareto-dominates the equilibrium of agents acting in autarky. However, as shown by D&D, demand deposit contracts also have a severe second equilibrium: as soon as sufficiently many depositors lose trust in their banks' solvency they coordinate on a second devastating equilibrium in which everyone prefers to withdraw deposits early. The bank then has to sell off assets at fire-sale prices and we end up in a bank run situation. We thus have a model of multiple equilibria; a *good* equilibrium in which the demand-deposit contract offers risk-sharing and a welfare increase and a *bad* equilibrium in which we observe panic-based bank runs that decrease welfare. Depositors face a coordination problem and a crisis occurs whenever depositors fail to coordinate on the good equilibrium.[3]

Since D&D a large strand of literature has emerged that focuses on the determination of the fundamentals/information driving the equilibrium selection. One rising strand of literature bases on the theory of global games that allow modeling coordination games in which thanks to a noisy private signal multiple equilibria are eradicated and a unique equilibrium results (Carlsson and Van Damme, 1993; Morris and Shin, 1998, 2001, 2004; Rochet and Vives, 2004). One particular application of global games theory developed by Goldstein and Pauzner (2005) focuses on the resolution of the multiple equilibria problem occuring in bank runs. This model will be the theoretical cornerstone of this paper.

[3]In the wake of the financial crisis in late 2007, banks themselves also faced coordination problems and failed to coordinate on the *good* equilibrium, when they ran into liquidity and solvency problems (Brunnermeier, 2009). At any time, banks can borrow short-term liquidity at the central bank's discount windows when they are able to pledge enough valid collateral. However, borrowing at the discount window is associated with the stigma that obtaining central bank money is a signal of weakness, i.e., that the borrowing bank is not credit-worthy enough to borrow on the interbank market. Similarly, banks with eroding capital, such as Lehman Brothers, could have strengthened their balance sheet by issuing new equity. However, being the only bank issuing equity could also be interpreted as a signal of desperation and thus be very costly. The former stigma was solved eventually in December 2007 by the Federal Reserve bank when they allowed financial institutions to bid anonymously for their repo loans. The coordinated bail-out programs in late 2008 may have circumvented the problem of equity issuances.

Goldstein and Pauzner (2005) present a model in which economic fundamentals define whether bank runs occur. Every agent in the model receives a private noisy signal about the fundamental health of the economy. This makes it possible to calculate the likelihood of a bank run which depends on the amount of risk-sharing of the short-term payment in a demand-deposit contract. Using the existence of dominance regions in both extremely good and bad states of the world, Goldstein and Pauzner (2005) prove that in between these extrema a unique switching threshold has to exist for which depositors withdraw their funds early (late) in case they observe a signal below (above) this threshold. They provide several valuable insights: panic-based bank runs still occur and are driven by bad expectations of patient investors. Patient agents withdraw their deposit early whenever they observe a signal below a certain threshold, whereby this threshold is increasing with an increase in risk-sharing by the bank.

A very similar global games model is proposed by Vives (2014) to investigate the reaction of market participants for different precisions of the signal that investors receive and risk aversion parameters of agents. He finds that less precise private information (a more noisy signal) as well as being a more risk averse agent leads to more sensible reactions of individual investors, i.e., requiring them to receive a higher signal in order not to run the bank.

Klos and Sträter (2013) build an experimental design based on the theoretical model by Goldstein and Pauzner (2005) to investigate the reaction of investors with respect to higher risk-sharing offered by the bank. They observe that investors apply threshold strategies as predicted by theory. However, while the global games theory would suggest drastic reactions to changes in risk-sharing, they observe only minor reactions in behavior that may better be explained by level-k approaches. Furthermore, they find that threshold levels do not change over time and experience.

In this paper, I use a simplified version of the experimental design proposed by Klos and Sträter (2013) to investigate several conjectures that are claimed to have an influence on the threshold level of investors. First, I use a priming treatment similar to the one used by Cohn et al. (2015) to test the effect of inducing higher risk aversion or fear. Second, I measure to what extent subjects use higher order beliefs when participating in a beauty contest derived from Nagel (1995). And third, I study the effect of a change of the precision of the private signal that agents receive in the global game.

As subjects I use students of a banking lecture that is being taught every year at the University of Zurich in the Bachelor's program. The subjects participate in the experiment as part of a mandatory homework assignment and are incentivized by gaining ECUs (experimental currency units) that may later be transformed into chocolate pralines in class. In the main treatment students assume the role of one out of six depositors of a bank and have to decide either to withdraw their investment either early or late depending a signal of the fundamental state of the economy.

I find that subjects that have been primed with a financial bust have a 32% higher odds ratio to withdraw early than subjects without priming. Similarly, depositors that were primed with a beauty contest before they participate in the bank run treatment have a 29% higher odds ratio to run on the bank. The probability of early withdrawal also increases for subjects that take higher order beliefs into account. Furthermore, I find evidence that less accurate private information increases the probability of a bank run.

The remainder of this paper is organized as follows: Section 1.2 gives a review of experimental finance literature in the context of bank runs. Section 1.3 covers the theoretical model of bank runs in general and the global games solution in particular. Section 1.4 introduces the experimental bank run design for which Section 1.5 presents empirical analysis. Section 1.6 concludes.

1.2 Literature

Investigating financial crises and bank runs in the context of experimental finance is a newly emerging and growing strand of literature. Madiès (2006) is among the first to use an experimental setup to study bank runs. He tests to what extent banking panics can be curbed through learning effects. In his experimental design he uses three different treatments: i) higher and lower values of the early payment to simulate "narrow banking", ii) a short or long suspension of convertibility of deposits once a run has started, and iii) a system of deposit insurance with either a coverage ratio of 25% or 75%. He finds that self-fulfilling bank runs are very common and recurring phenomena. However, the likelihood of a bank run can be reduced by temporary suspension of convertibility of demand deposits combined with narrow banking. To prevent panics completely, he suggests that full deposit insurance might be required.

Schotter and Yorulmazer (2009) and Garratt and Keister (2009) test the impact of information in a sequential move bank run model. Schotter and Yorulmazer (2009) implement a sequential decision game where depositors choose to withdraw in one out of four subsequent periods. There are several treatments in their study to test the sensitivity of depositors to i) low or high information availability, ii) asymmetric information distribution, and iii) existence of deposit insurance. They find that depositors that are able to observe the behavior of other depositors (high information availability) are less likely to withdraw their deposits early. If there is an "insider" in the group, i.e., a depositor that knows the true quality of the bank, the likelihood of a banking crisis is reduced and coordination of all depositors is increased. Finally, they also show that deposit insurance helps curb the severity of a bank run. On the other hand, Garratt and Keister (2009) also study the effects of adding uncertainty about fundamental withdrawal but use i) changing number of opportunities in which depositors are able to withdraw their funds and ii) add players that are randomly chosen and forced to withdraw early (similar to impatient agents in the model of D&D). They confirm the results of Schotter and Yorulmazer (2009) that panic frequency drops once withdrawal behavior is made transparent. In addition, they find that subjects have a higher probability to run on the bank if they have more opportunities to do so. Furthermore, adding stochastic withdrawal demand (forcing a random number of depositors to withdraw) increases the overall likelihood of bank runs.

Kiss et al. (2012) implement a bank run model in which depositors decide sequentially whether they want to withdraw their money. This allows them to study how observability of actions of other depositors affects the probability of a bank run while controlling for different levels of deposit insurance. They find that observability and deposit insurance both reduce the probability of bank runs. In two later publications, the same authors first restrict the observability of actions to the condition of being in the same social network (Kiss et al., 2014a) and second highlight gender differences (Kiss et al., 2014b). The probability of withdrawal decreases for the first to decide if the action is being observed by the second depositor in a sequential game. In general, they do not find evidence that women react differently from men. Gender only makes a difference if withdrawal decisions is being observed by other depositors. Furthermore, they do not find evidence that risk aversion has explanatory power for investors' decisions.

Arifovic et al. (2013) set up an experimental bank run model to study whether coordination failures causes depositors to withdraw funds. Specifically, they measure the effect of exogenous changes in the required fraction of late withdrawing depositors needed to keep a bank liquid. This generates a variation in the complementarity of coordinated actions. They are able to show that there is a coordination parameter threshold at around 70%, i.e., coordination fails more often if there are more than 70% of all depositors required to withdraw late in order to prevent a bank run. For lower parameters coordination is perceived as easier and bank runs are less frequently.

Chakravarty et al. (2014) and Brown et al. (2016) investigate the mechanisms behind bank run contagion, i.e., whether runs on one bank may trigger runs on another bank. Both studies use a model based on D&D with two banks that are either economically linked or independent. Before depositors of the first bank may decide to withdraw their funds they receive information about the level of liquidity of their bank (Chakravarty et al., 2014) or the liquidating value of the long-term asset of the bank (Brown et al., 2016). Depositors of the other bank only observe the withdrawal decisions of the depositors of the first bank. Clearly, depositors of the first bank show higher withdrawal rates if liquidity is low or if fundamentals are weak. If the two banks have economic linkages, withdrawal rates of the second bank increase if depositors observe high withdrawal rates at the first bank. More interestingly, the two studies differ when there are no economic linkages between the banks. Only Chakravarty et al. (2014) find a positive contagion effect between banks without economic linkages. This might indicate that panic-based contagion can rather be explained by liquidity problems than by low long-term asset returns.

A similar experimental setup has been used by Dijk (2015) to study the impact of inducing emotional states on the likelihood of a panic-based bank run. Before subjects participate in the main bank run treatment he lets them write a short essay of a particularly fearful, sad, or happy memory. He finds that subjects that have been induced with a target emotion of fear are significantly more likely to withdraw their deposits early. Female subjects in the fear treatment react stronger than men. While sadness decreases the likelihood of a bank run, happiness does not change the withdrawal behavior of depositors.

1.3 Theoretical Analysis of the Bank Run Model

1.3.1 Formal Framework

Models of bank runs are coordination games with strategic complementarities under incomplete information that usually lead to multiple equilibria: a good equilibrium where depositors trust the bank, and a bad equilibrium where depositors loose trust and run on the bank. One way to eradicate the multiple equilibria problem in coordination games is the implementation of global games. The framework and notation used in this section are based on the global games approach by Goldstein and Pauzner (2005) that extends the seminal paper by D&D. The model has three periods ($t = 0, 1, 2$) and a continuum of consumers $[0, 1]$ that are all equally born in $t = 0$ with an endowment of a single unit of a homogeneous good. Agents may consume in period 1 or 2, where c_t denotes consumption level in period $t \in \{1; 2\}$. Consumption goods can be transferred from one period to another without loss (e.g. by storing it). With a probability λ an agent is impatient and with $1 - \lambda$ she is patient. Agents learn their type at the beginning of $t = 1$ as a private information. Impatient agents can only derive utility from consumption in $t = 1$, i.e. $u(c_1) > 0$, while patient agents can derive utility in both periods ($u(c_1 + c_2)$). The utility function $u(c)$ is twice continuously differentiable and has an Arrow-Pratt measure of relative risk aversion $-cu''(c)/u'(c) > 1$ for any $c \geq 1$.

Agents deposit their endowment in a productive technology that may be liquidated in $t = 1$ or $t = 2$. In $t = 1$, the technology gives one unit of output per unit of input, i.e., there is no loss from early liquidation. Per unit of input the long-term investment (until $t = 2$) yields R units of output with probability $p(\theta)$, or 0 with probability $(1 - p(\theta))$, where θ denotes the fundamental state of the economy drawn in $t = 0$ from a uniform distribution $\theta \sim \mathcal{U}[0, 1]$ with $p'(\theta) > 0$. Agents do not learn the true value of θ until $t = 2$. In expectation, long-term investment dominates early liquidation, i.e. $\mathbb{E}_\theta[p(\theta)]u(R) > u(1)$.

In autarky, impatient agents would liquidate the project in $t = 1$ and consume one unit while patient agents leave their money invested and consume R in $t = 2$ with probability $p(\theta)$ and 0 with probability $(1 - p(\theta))$. As shown by Bryant (1980) and D&D, due to risk aversion a contract that offers risk sharing by a transfer from patient to impatient agents could, ex ante, be beneficial to all agents. Assume for a moment that types are third-party verifiable. A social planner would choose c_1 such that overall utility $\lambda u(c_1) + (1 - \lambda)u\left(\frac{1-\lambda c_1}{1-\lambda} R\right) \mathbb{E}_\theta[p(\theta)]$ is maximized. λc_1 denotes the amount of early liquidation needed to satisfy the impatient agents, $(1 - \lambda c_1)$ remains invested in the production technology and yields a return of R that will be distributed pro rata among the $(1-\lambda)$ patient agents. This allows the social planner to determine first-best c_1^{FB} using the first-order condition (FOC):

$$u'(c_1^{FB}) = Ru'\left(\frac{1 - \lambda c_1^{FB}}{1 - \lambda} R\right) \mathbb{E}_\theta[p(\theta)]. \tag{1.1}$$

The marginal benefit of impatient agents (LHS) equals marginal costs of patient agents (RHS). Since $cu'(c)$ decreases in c (by assumption of $RRA > 1$) and $\mathbb{E}_\theta[p(\theta)] < 1$, the marginal benefit at $c_1 = 1$, $u'(1)$, exceeds the marginal costs, $Ru'(R)\mathbb{E}_\theta[p(\theta)]$. Thus, in the social optimum there is risk sharing with $c_1^{FB} > 1$. This means that ex ante patient agents agree to give up some consumption to insure against the risk of experiencing a liquidity shock (being of the type 'impatient').

1.3.2 Demand-Deposit Contracts and Multiple Equilibria

The social planner above optimized c_1 assuming agents' types are observable. Unfortunately, types are private information and agents cannot write enforceable contracts upon being impatient or not. As illustrated by D&D, banks offer such risk-sharing in the form of demand-deposit contracts. In such a contract every agent deposits her initial endowment with the bank at $t = 0$. The bank offers a payment of $r_1 > 1$ to all agents that want to withdraw at $t = 1$ and a stochastic payment $\tilde{r}_2$ at $t = 2$ to all remaining agents. The payment $\tilde{r}_2$ depends both on the state of the economy, θ, and on the fraction of agents that withdraws early, defined as n. Payment in $t = 1$ is subject to a *sequential service constraint*: depositors are lined up randomly and paid out as long as the bank is solvent.

Assume that the bank sets $r_1 = c_1^{FB}$. As long as only impatient agents withdraw in $t = 1$, i.e. $n = \lambda$, the expected utility for patient agents is $u\left(\frac{1-\lambda r_1}{1-\lambda} R\right) \mathbb{E}_\theta[p(\theta)]$. If this is larger than $u(r_1)$, patient agents have no incentive to withdraw in $t = 1$ and we achieve the first-best equilibrium by the social planner. However, as D&D illustrate, if all agents were to decide to withdraw in $t = 1$ ($n = 1$), the bank would need to liquidate all assets, the expected payment in $t = 1$ is $1/r_1$ and there will be no payment in $t = 2$. This is the bank run equilibrium in which no patient agent has an incentive to withdraw late. Panel A in Table 1.1 illustrates the general theoretical ex post payoff matrix from the demand-deposit contract depending on θ and n.

INSERT TABLE 1.1 AROUND HERE.

This second equilibrium is even inferior to the payoff structure in autarky. What drives depositors to coordinate on the bad equilibrium? In the model by Diamond and Dybvig (1983, p. 410) it is assumed that "...anything that causes [depositors] to anticipate a run will lead to a run." This may be related both to fundamentals of the bank or to any other coordination device such as runs on other banks, bad news in the media, or even sunspots. Nevertheless, there is no prediction on which equilibrium agents will coordinate.

1.3.3 Global Games: Introduction of Private Noisy Signals

Goldstein and Pauzner (2005) solve the multiple equilibria problem in the traditional bank run model by introducing a private signal about the fundamental state of the economy. In their model θ is established at the beginning of $t = 1$ but not publicly observable until $t = 2$. However, all individuals i receive private noisy signals $\theta_i = \theta + \epsilon_i$, where ϵ_i is a i.i.d. small error term in $[-\epsilon, \epsilon]$ with a uniform distribution.

Patient agents infer from the private signal θ_i firstly a belief about the true state of the economy θ and secondly a belief about the distribution of signals that other agents may have received. The signal acts as a coordination device for equilibrium selection: extremely low signals diminish the probability that the production technology yields R and increases the incentive to withdraw early and, vice versa, extremely high signals increase the incentive to withdraw late. Goldstein and Pauzner (2005) show that in between these ranges there is a unique switching point θ^* for which agents withdraw early (late) if their signal is below (above) this threshold. This result can be derived as follows: assume that dominance regions exist, i.e., there are ranges of extreme values of signals θ_i for which the behavior of patient agents is independent of other agents' actions. This results in all agents withdrawing for very bad signals and no patient agents withdrawing for very good signals. For signals close to these extreme values agents take the best actions at the corresponding extreme end into account. Signals farther away makes depositors consider best actions for signals nearby. Eventually, closing the gap from above and below, a unique equilibrium with a threshold value emerges for which signals below lead to early, and signals above lead to late withdrawal while signals equal to the threshold lead to indifference.

Let $\underline{\theta}(r_1)$ denote the value for which $u(r_1) = p(\theta)u((1-\lambda r_1)/(1-\lambda)R)$. For any fundamental value θ in the interval $[0, \underline{\theta}(r_1))$ the probability of default is so high that the expected utility from withdrawal at $t = 2$ is lower than withdrawing at $t = 1$ irrespective of what other depositors do. This range is the so-called *lower dominance region.* However, true fundamentals are not observed at $t = 1$: An agent only receives a noisy signal θ_i and thus only knows that she is located within the lower dominance region if she observes a signal $\theta_i \in [0, \underline{\theta}(r_1) - \epsilon)$. The same analysis for the *upper dominance region* leads to an interval $(\bar{\theta}(r_1), 1]$, where an agent that receives a signal $\theta_i \in (\bar{\theta}(r_1) + \epsilon, 1]$ will always wait until $t = 2$, regardless of the other agents' actions.

The fraction n of how many agents withdraw early depends on the fraction of impatient agents λ, and the fraction of patient agents withdrawing early. The latter use the signal θ_i to infer two ranges: an interval for the true fundamental, $\theta \in [\theta_i - \epsilon, \theta_i + \epsilon]$, and an interval for signals that any other depositor j might have received, $\theta_j \in [\theta_i - 2\epsilon, \theta_i + 2\epsilon]$. In the interval $[\underline{\theta} - 2\epsilon, \underline{\theta})$ a depositor thus assigns a positive probability that other depositors have received private signals equal to or above $\underline{\theta} - \epsilon$. The higher θ the lower the probability that other agents received signals in the lower dominance region and the lower the fraction of patient agents withdrawing early. As the noise term ϵ_i is uniformly distributed, the fraction of patient agents that receive signals below $\underline{\theta} - \epsilon$ linearly decreases in θ.

To derive the optimal threshold first assume that a unique equilibrium for which patient agents withdraw early only if they receive a signal below a threshold $\theta^*(r_1)$ exists. Given this equilibrium, the fraction of depositors that withdraw early depends on the fundamental state of the economy θ and equals:

$$n(\theta, \theta^*(r_1)) = \lambda + (1-\lambda)p\left[\epsilon_i < (\theta^*(r_1) - \theta)\right], \tag{1.2}$$

where the first term on the RHS equals all impatient agents, λ, and second term is the expected fraction of patient agents with signals falling below the threshold value $\theta^*(r_1)$. If the fundamental value θ is below $\theta^*(r_1) - \epsilon$, all patient agents withdraw early. Fundamentals above $\theta^*(r_1) + \epsilon$ leave only the impatient agents withdrawing early. In between these values the fraction of patient agents descreases linearly in θ due to the uniform distribution of the noise term ϵ:

$$n\left(\theta,\theta^*(r_1)\right)=\begin{cases}1 & \text{if} \quad \theta\le\theta^*(r_1)-\epsilon\\ \lambda+(1-\lambda)\left(\frac{1}{2}+\frac{\theta^*(r_1)-\theta}{2\epsilon}\right) & \text{if} \quad \theta^*(r_1)-\epsilon\le\theta\le\theta^*(r_1)+\epsilon\\ \lambda & \text{if} \quad \theta\ge\theta^*(r_1)+\epsilon.\end{cases} \tag{1.3}$$

Goldstein and Pauzner (2005) prove that the signal θ_i acts as the single coordination device in equilibrium selection with a unique threshold value θ^*.[4] To derive the threshold value θ^* they compute the utility differentials between withdrawing in period 2 compared to period 1 based on the payoffs in Table 1.1:

$$v(\theta,n)=\begin{cases}p(\theta)u\left(\frac{1-nr_1}{1-n}R\right)-u(r_1) & \text{if} \quad \lambda\le n\le\frac{1}{r_1}\\ 0-\frac{1}{nr_1}u(r_1) & \text{if} \quad \frac{1}{r_1}\le n\le 1.\end{cases} \tag{1.4}$$

Withdrawal in period 2, $p(\theta)u\left(\frac{1-nr_1}{1-n}R\right)$, yields the highest utility if only the impatient agents withdraw in period 1, i.e. $n=\lambda$. For an increase in n, waiting becomes less attractive until for $n=1/r_1$ the bank has to declare bankruptcy and payoff in period 2 is null. Unlike traditional global games approaches, see, e.g., Carlsson and Van Damme (1993) or Morris and Shin (1998, 2001), we only have *one-sided* instead of *global strategic complementarities*, i.e., the more agents decide to withdraw late the more attractive it becomes for other agents to withdraw late too. For early withdrawal, however, the incentive of a patient agent to withdraw early is highest if the bank has just declared bankruptcy, i.e., when $n=1/r_1$. If the bank is bankrupt, the more depositors demand their deposit the lower the probability to receive payment r_1 and therefore the incentive to withdraw early decreases. This can be seen in Figure 1.1 that shows the utility differential of withdrawing late rather than early for any fraction n of agents withdrawing in period 1.

INSERT FIGURE 1.1 AROUND HERE.

As Goldstein and Pauzner (2005) have shown, it suffices to prove that the utility differential function v crosses zero only once to prove the uniqueness of the threshold strategy θ^*. To calculate θ^* we assume that all patient agents use a common threshold θ'. Since the signal is noisy, any agent that receives a signal θ_i, calculates the expected utility differential $\Delta^{r_1}(\theta_i,\theta')$ from withdrawal in period 2 versus period 1 as the average utility differential over $[\theta_i-\epsilon,\theta_i+\epsilon]$:

$$\Delta^{r_1}(\theta_i,\theta')=\frac{1}{2\epsilon}\int_{\theta_i-\epsilon}^{\theta_i+\epsilon}v\left(\theta,n(\theta,\theta')\right)d\theta. \tag{1.5}$$

[4]This is in contrast to the proclaimed sunspot theories as in Williams (1961) or Cass and Shell (1983).

Whenever $\Delta^{r_1}(\theta_i, \theta')$ is positive, a patient agent should reduce the threshold value as a best response to θ' and, vice versa, increase the threshold if $\Delta^{r_1}(\theta_i, \theta')$ is negative. In equilibrium we must have $\Delta^{r_1}(\theta', \theta') = 0$. Due to the single crossing condition, this only holds for the unique threshold equilibrium θ^*.

1.4 Experimental Design and Predictions

This article is based on one main and three auxiliary experimental treatments. A flowchart of the whole experiment with the order of the individual treatments and treatment assignment path of subjects is shown in Figure 1.2. Detailed treatment instructions as well as all questionnaires are provided in Appendix A.1.

Insert Figure 1.2 around here.

The main treatment, called the *Bank Run Treatment*, uses a simplified version of the experimental bank run model of Klos and Sträter (2013) based on Goldstein and Pauzner (2005). Subjects are in a coordination game with incomplete information where their payoff depends on their action, the actions of other subjects, and on the state of the world. Subjects assume the role of depositors and have to make a binary decision whether they want to withdraw their investment early or wait. As basis for their decision they receive private noisy signals about the fundamental state of world. In this treatment I am able to identify whether subjects employ a threshold strategy and where the most likely threshold value lies.

The second treatment is a *Priming Treatment* in which subjects are asked to fill in a short questionnaire with investment tasks. Subjects are shown charts that either resemble a stock market boom or a bust and have to answer simple questions about optimal investment behavior in these situations. This questionnaire primes the subjects and renders the situation of a boom or bust mentally salient. The treatment is based on Cohn et al. (2015) who showed that subjects' risk-aversion is countercyclical, i.e., subjects in a bust exhibit higher risk-aversion than subjects in a boom treatment. In this experiment, individuals are assigned to one of three sub-treatments: 1) boom treatment, 2) bust treatment, or, as a control treatment, 3) no priming. Chronologically the priming takes place before the main bank run treatment.

Global games theory requires that individuals take higher order beliefs into account, i.e., the beliefs about other individuals' beliefs about other individuals' beliefs ... *ad infinitum*. In the third treatment, I want to test to what extent subjects perform this so-called *level-k thinking*. To do this I use the most prominent example of beauty contest games: the *Guess the Number Treatment* (GTN) that was proposed by Nagel (1995). Subjects in this treatment simultaneously have to pick a number in the interval $[0, 100]$ such that it comes closest to 2/3 of the average of all picked numbers. The more sophisticated a subject is and the more the subject believes that the other subjects are sophisticated too, the lower should the guessed number be. The eventual Nash equilibrium would be zero. However, subjects usually only employ a finite number of iterations k. Since playing the GTN game has a priming effect in itself I randomize the order in which the bank run treatment and the guess-the-number treatment are played. This allows me to use the order of the games as a treatment in itself.

The last treatment is a variation of the main bank run treatment. Vives (2014) shows in a very similar bank run model that an increase in the noise of the private signal leads to larger sensitivity of subjects to bad signals, i.e., increases the threshold value required for coordination on the good outcome. I test this experimentally by increasing the range of the noise term ϵ.

At the end of the experiment, subjects are asked to fill in a questionnaire with a risk-aversion elicitation question, questions about the experiment as well as demographic and study-related details.

1.4.1 Bank Run Treatment

The *Bank Run Treatment* (BR) is the main treatment of this paper. It is based on the global games bank run model by Goldstein and Pauzner (2005) and uses a similar parametrization as in Klos and Sträter (2013). A timeline of the BR treatment is depicted in Figure 1.3. At the beginning of a period every subject is randomly assigned to a group of six investors.[5] Every investor deposits 1 ECU in the bank. The total of 6 ECUs is then being invested by the bank in a risky project that yields an uncertain return R in $t = 2$. The bank promises a payment of 1.5 ECU to any depositor that decides to withdraw early (in $t = 1$). I assume that ex ante there is no impatient agent in the setup, i.e. $\lambda = 0$. If there is a positive number of early withdrawers ($n > 0$) the bank has to liquidate a part of the investment ($n \times 1.5$) in order to repay the impatient subjects in $t = 1$. If four or more depositors decide to withdraw early ($n \times 1.5 \geq 6$), we have the case of a bank run, the bank has to liquidate the full project and declares bankruptcy.[6] If three or less

[5] A group size of $N = 6$, i.e., a bank that is funded by six depositors only, is an extreme case compared to traditional atomistic-sized individual depositors that we usually see in banking. The impact of such a small group size is that a depositor in this model rather equals an institutional investor than a depositor. Furthermore, six seems to be a reasonable size weighing off reality and experimental simplification. The experimental bank run studies by Schotter and Yorulmazer (2009) and Klos and Sträter (2013) also form groups of six depositors.

[6] In case of $n = 5$ or $n = 6$ early withdrawers, four investors are randomly selected and receive the payment of 1.5. The other early withdrawer(s) receive nothing. This mechanism is a way to model the sequential service constraint (SSC) in $t = 1$.

depositors decide to withdraw early, the bank remains solvent and liquidates the project in $t = 2$. The proceeds of the final liquidation is distributed evenly among the remaining depositors.

INSERT FIGURE 1.3 AROUND HERE.

At the beginning of $t = 1$, every investor receives a noisy signal regarding the fundamental range of the project return R. Goldstein and Pauzner (2005) model the project return as a mapping function of the fundamental θ that defines 'success' or 'failure' of the production technology, $p(\theta) : \mathbb{R} \longrightarrow [0, 1]$. This paper uses a simplification and parametrization similar to Klos and Sträter (2013) and define the fundamental state of the economy as the uniformly distributed project return $\theta \equiv R$ where $R \sim \mathcal{U}(1.3, 3.0)$. The signal investors receive is private and noisy with uniform distribution $\epsilon \sim \mathcal{U}(-0.1, 0.1)$ (or $\epsilon \sim \mathcal{U}(-0.3, 0.3)$ in the *noisy* treatment).

The return of any investor thus depends on the individual and on the collective withdrawal decision in period $t = 1$. This coordination problem is illustrated in Panel B in Table 1.1. If an investor decides to withdraw in $t = 1$ and less than three other depositors withdraw early (in total $n < 4$) the early repayment is $r_1 = 1.5$. Whenever a total of four or more depositors ($n \geq 4$) decide to withdraw early, we have the situation of a bank run and the repayment is $r_1 = 1.5$ with probability $4/n$, and zero otherwise. If a depositor waits until $t = 2$ and there was no bank run in $t = 1$ the repayment is $R(6 - n \times 1.5)$, i.e., the realized return of the project times what was left invested after period 1. If there was a bank run in $t = 1$, the payment late withdrawers receive is zero.

One period in the BR model consists of two stages. A *decision* stage and a *results* stage. In the decision stage every investor receives the private noisy signal, θ_i, that indicates the range of the true fundamental $R \in [\theta_i - \epsilon, \theta_i + \epsilon]$. Since it would be very time-consuming for an experimental subject to compute potential payoffs for any given fundamental they are presented with an extended payoff table in the decision stage. This table shows the individual payoffs for any given number of early withdrawers assuming that $R = \theta$. A sample payoff table with $\theta = 2.0$ is depicted in Table 1.2.

INSERT TABLE 1.2 AROUND HERE.

The payoff of one investor thus depends on the decision to withdraw early or late and on the withdrawal decisions of all other depositors. Given the case of $\theta \geq 1.50$, investors have an incentive to coordinate on the same action, i.e., every investor wants to stay with the bank until $t = 2$ as long as enough other depositors decide to stay as well. In case of $\theta < 1.50$ we have the situation of a fundamental bank run where withdrawing early becomes a dominant strategy irrespective of the behavior of the other depositors. For any $\theta < 1.5$ we are located in the *lower dominance region*.[7]

The optimal threshold θ^* is derived similar to Heinemann et al. (2004) and Klos and Sträter (2013). The computation is based on three steps: 1) describe the probability that a patient agent j withdraws early given that agent i receives signal θ_i and assuming that a common threshold θ' exists, 2) derive the expected utilities from early and late withdrawal for any given signal θ_i, 3) compute the numerical optimal threshold θ^* by iterated elimination of dominated strategies θ'.

For the first step, assume that a common threshold θ' is given exogenously, i.e., any depositor i withdraws early if and only if the signal θ_i received in $t = 1$ is below this threshold. From the signal θ_i, the depositor i can infer the range of the true fundamental $\theta (= \theta_i \pm \epsilon)$ and the range of signals that other depositors may receive $(= \theta_i \pm 2\epsilon)$. Since the fundamental and the noise term are uniformly distributed, the distribution of signals that any other depositor j may have received is a symmetrical triangular distribution with mean θ_i and range $[\theta_i - 2\epsilon, \theta_i + 2\epsilon]$. The probability that depositor j withdraws early (denoted by 'withdraw') given a common threshold θ' and a signal θ_i for depositor i is thus:

$$\mathrm{P}(\text{withdraw}|\theta_i, \theta') = \mathrm{P}(\theta_j < \theta'|\theta_i, \theta') = \begin{cases} 0 & \text{if } \theta' < \theta_i - 2\epsilon \\ \frac{(\theta' - (\theta_i - 2\epsilon))^2}{8\epsilon^2} & \text{if } \theta_i - 2\epsilon \leq \theta' < \theta_i \\ 1 - \frac{(\theta_i + 2\epsilon - \theta')^2}{8\epsilon^2} & \text{if } \theta_i \leq \theta' < \theta_i + 2\epsilon \\ 1 & \text{if } \theta_i + 2\epsilon \leq \theta'. \end{cases} \tag{1.6}$$

In the second step, expected utilities of early withdrawal and late withdrawals are derived. For early withdrawal, the expected utility corresponds to the sum of expected utilities that none, one, ..., or all of the other $N - 1$ investors withdraw early, weighted with the corresponding probability:

$$\mathrm{EU}_{\text{withdraw}}(\theta_i, \theta') = \sum_{n=0}^{N-1} \frac{1}{2\epsilon} \int_{\theta'-\epsilon}^{\theta'+\epsilon} \mathcal{B}\left(n, N-1, \mathrm{P}(\text{withdraw}|\theta_i, \theta')\right) \mathbb{E}(\mathrm{U}_{\text{withdraw}}|n) d\theta_i. \tag{1.7}$$

The term $\mathcal{B}(n, N-1, \mathrm{P}_{\text{withdraw}}(\theta_i, \theta'))$ denotes the binomial probability that exactly n out of $N - 1$ other depositors receive a signal below the threshold θ' given the signal θ_i of depositor i. Since the true fundamental is unknown we integrate over all possible values

[7]The lower dominance region is defined as $[1.3, 1.5)$. This model lacks an upper dominance region in which no investor has an incentive to withdraw early. However, as Goldstein and Pauzner (2005, Appendix B, p. 1325) point out, the condition of having an upper dominance region may be neglected as long as three reasonable refinement criteria are met: (a) agents coordinate on the Pareto-dominant equilibrium, (b) agents coordinate on the no-run equilibrium for very high signals, and (c) agents coordinate on an equilibrium that has monotonic strategies and individual actions depend on received signals.

for $\theta \in [\theta_i - \epsilon, \theta_i + \epsilon]$ and scale by the width of the range 2ϵ. The expectation of utility $\mathrm{U}_{\text{withdraw}}$ depends only on n and equals:

$$\mathbb{E}(\mathrm{U}_{\text{withdraw}}|n) = \begin{cases} u[1.5] & \text{if} \quad n < 4 \\ u[1.5 * (4/n)] & \text{if} \quad n \geq 4. \end{cases} \tag{1.8}$$

The expected utility from early withdrawal does not depend directly on the exact realization of the fundamental θ. The fundamental only defines the range of signals which in turn defines the probability of early withdrawal. On the other hand, the expected utility from late withdrawal (denoted by 'wait') does depend on θ. It may be calculated analogously:

$$\mathrm{EU}_{\text{wait}}(\theta_i, \theta') = \sum_{n=0}^{N-1} \frac{1}{2\epsilon} \int_{\theta'-\epsilon}^{\theta'+\epsilon} \mathcal{B}\left(n, N-1, \mathrm{P}(\text{withdraw}|\theta_i, \theta')\right) \mathbb{E}(\mathrm{U}_{\text{wait}}|n, \theta_i) d\theta_i. \tag{1.9}$$

The only difference between Equation 1.9 and Equation 1.7 is the last term. The expected utility of waiting depends both on the number of early withdrawers n as well as on the true fundamental θ. However, since a depositor does not know θ we integrate over the possible range ($[\theta_i - \epsilon, \theta_i + \epsilon]$) and use the simplification that $\theta_i \equiv R$:

$$\mathbb{E}(\mathrm{U}_{\text{wait}}|n, \theta_i) = \begin{cases} u[\theta_i(6 - n \times 1.5)] & \text{if} \quad n < 4 \\ 0 & \text{if} \quad n \geq 4. \end{cases} \tag{1.10}$$

In the third step to derive the optimal threshold θ^* we use iterative elimination of dominated strategies. So far it was assumed that all investors use a common threshold θ'. Consider investor i who receives a private signal θ_i. If $\theta_i \leq \theta'$ and $\mathrm{EU}_{\text{withdraw}}(\theta_i, \theta') < \mathrm{EU}_{\text{wait}}(\theta_i, \theta')$ it would be optimal for i to wait with withdrawal until $t = 2$ since the expected utility from waiting is higher than the expected utility from withdrawing early. Investor i should thus use a higher threshold. The best-response of investor i is $\theta_i^* = \mathrm{BR}(\theta')$. Since all investors are homogeneous we can eliminate θ' as a threshold strategy and conduct the same analysis with the next higher threshold value. We iterate this procedure until we have $BR(\theta^*) = \theta^*$. The optimal threshold thus solves $\mathrm{EU}_{\text{withdraw}}(\theta^*, \theta^*) = \mathrm{EU}_{\text{wait}}(\theta^*, \theta^*)$.

1.4.2 Additional Treatments

1.4.2.1 Priming Treatment

The first additional treatment is a priming treatment on risk preferences that is played at the beginning of the experiment. Priming is a method that has long been used primarily in psychology and has become increasingly popular in economics and banking to study changes of preferences and behavior of subjects in different environments.[8] Closely related to this study, Dijk (2015) uses a priming treatment to induce background fear, sadness or happiness before participants participate in a bank run game. He observes that subjects primed with fear exhibit a higher likelihood to loose trust and run on the bank.

I use a priming procedure that has successfully been applied by Cohn et al. (2015) to investigate the reaction of financial professionals after increasing the subjects' saliency of financial booms and busts. Subjects in their experiment are filling in a questionnaire before they let the participants play risky lotteries. They find that individuals that have been answering questions about their hypothetical behavior in a bust scenario are emotionally negatively affected compared to individuals in a boom scenario. Subjects in the bust treatment have a significantly decreased willingness to take risks. This helps explain countercyclical risk aversion that can be observed in financial markets, i.e., higher equity risk premia in recessions compared to booms. If households have a higher risk aversion in downturns and require a higher equity risk premium this might lead to an adverse and self-reinforcing feedback loop. If stock prices fall this could arouse fear and higher risk aversion among investors. Investors would then sell their assets and depress markets and increase risk aversion even further (Cohn et al., 2015).

This paper uses a similar priming treatment to induce a change in risk preferences and the emotion of fear of subjects before they play the BR treatment. First, subjects are randomly assigned to either a *Boom* or a *Bust Treatment*, or receive no treatment at all (this is a control treatment, called *No Priming*). In the boom and bust treatments they start with an identical priming introductory questionnaire intended to warm up and make subjects salient to investment decisions.[9] In the main priming part, subjects in the boom (bust) treatment are presented with a green strongly rising (red sharply decreasing) stock market price chart. At the end of the price charts an arrow points upwards (downwards) to indicate the expected trend in the near future. This chart is followed by three subsequent questions whether the subject would rather buy or sell shares / gold / real estate. The questions do not differ in the two treatments. The priming treatment ends with a short final questionnaire to elicit subjects' affective state (ranging from 'very negative' to 'very positive' on a nine-point scale of manikins proposed by Bradley and Lang (1994)) and emotion of fear (ranging from 'not at all' to 'a lot' on a seven-point Likert scale).

[8]See Bargh and Chartrand (2000) for a general practical guide and Cohn and Maréchal (2016) for a survey of the use of priming in economics. Cohn et al. (2014) provides an application of priming in the context of banking: They measure honesty of bank employees after reminding them of their occupational role.

[9]See Appendix A.1.2 for the original questionnaire as well as all instructions.

Higher risk aversion increases the optimal threshold θ^* subjects should use in the BR treatment to decide whether to withdraw early or late. We should thus observe a lower (higher) probability of bank runs in the subsequent BR treatment if subjects have been primed with a boom (bust) treatment. Banking crises possess self-reinforcing feedback loops too; experiencing a bank run (loss of wealth) could evoke fear among depositors and render them more risk averse. Higher risk aversion in turn increases the likelihood of inefficient panic-based bank runs (due to the higher required fundamental θ to trust the bank). The priming treatments provide a test whether a boom or bust sparks positive feedback loops in banking crises.

1.4.2.2 Guess the Number Treatment

The second additional treatment in this study is an implementation of a so-called 'beauty contest' or 'guessing game' (see, e.g., Duffy and Nagel (1997); Ho et al. (1998); Nagel (1995); Stahl and Wilson (1995)).[10] This game builds on the belief of subjects to have an above average ability to identify best responses to actions of other subjects, i.e., to think one step further than the average of all other subjects does. In the most commonly used game, participants are asked to simultaneously pick a number in the closed interval of $[0, 100]$. The participant that comes closest to the arithmetic average of all picked numbers multiplied with a factor p is the winner. The parameter p is predetermined and common knowledge. In case of a tie, the payoff is divided equally.

For any parameter p in the range $[0, 1)$ it is obvious that there is only one Nash equilibrium: all subjects pick *zero*. Experimental evidence, however, repeatedly showed that players only employ bounded rational strategies.[11] The winning number usually is significantly larger than zero. Assume, we set $p = 2/3$. In the simplest case, a subject randomly chooses a number in the interval $[0, 100]$. This player assumes a uniform distribution for the winning number and randomly chooses an estimate. This player is called the 'level-0 thinking player' and in expectation picks the number $(0 + 100)/2 = 50$. The next higher order player forms a belief that all other participants are level-0 players and

[10] The name 'beauty contest' for this category of strategic game has been coined by John Maynard Keynes, who described an analogy of the behavior of investors on the financial markets with the newspaper beauty contests where readers were asked to bet on the six prettiest faces out of a hundred photographs. The winner of the newspaper beauty contest would be the person whose bets were closest to the average bets of all other participants. A participant has to pick the photographs that she thinks all others would pick too. This is not necessarily the person she thinks is prettiest nor even the average person would think is prettiest. Rather the winning photograph might be on a higher degree where a person forms beliefs about what the average expects the average opinion to be. As Keynes states it: "And there are some, I believe, who practise the fourth, fifth and higher degrees" (Keynes, 1936, p. 140). Analogously, stock traders might not be concerned primarily about the stock they think is most valuable. Rather they try to anticipate what the average trader expects other traders to value the most.

[11] For a general survey see, e.g., Camerer (2003); Camerer et al. (2004) or Kahneman (2003).

chooses $p^1 50 = {}^2\!/_3 50 = 33.33$. In general, the level-$k$ thinking player chooses $p^k 50$ as best-response to the $(k-1)$ order beliefs of all other players.

Nagel (1995) shows experimentally that in the first round players deviate strongly from the game-theoretic prediction. Most frequently, individuals only conducted one to two orders of higher beliefs, i.e., $k = 1$ or $k = 2$. Similarly, Camerer et al. (2004) find that players on average perform 1.5 steps in most higher order games. However, Nagel (1995) finds that after some rounds players use their experience and approach Nash equilibrium strategies.

The theoretic global games solution in the BR treatment builds on the assumption that individuals are able to perform $k = \infty$ steps and build infinitely higher order beliefs. The more sophisticated a depositor is and the more she believes that other depositors are sophisticated too the higher the degree of rationality and thus the closer is the strategic behavior in line with the global games solution. This treatment allows measuring level-k thinking on banking crises, i.e., whether more rational behavior increases the likelihood of bank runs. Depending on how many iterations k a subject performs the more I expect her to alter her expectation about the behavior of other investors in the BR game.

The experimental implementation of the GTN treatment consists of two rounds. In a first round, subjects have no prior information regarding the behavior of other subjects. The range of numbers lies in $[0, 100]$ and subjects are asked to pick the number that comes closest to $2/3$ of the average of all picked numbers. This first round is intended as a warm-up exercise to help subjects understand the game and build a strategy when picking a number. Since the guessing game is relatively well-known among students and many even know the Nash equilibrium from their studies, they subsequently pick zero.[12] A potential explanation for this could be that rather than trying to win the game subjects want to show that they understood the principle behind the Nash equilibrium in this game. To show the subjects that it is not necessarily the player who chooses the Nash equilibrium that wins the game I present the participants with the winning number of a previous experimental study.[13] This number provides a common knowledge starting point for the second round.

To obtain the numeric level k, I simply solve $50p^k = x_i$ for k where x_i represents the picked number of individual k, i.e. $k = \ln(x_i/50)/\ln(p)$. Later on, in the empirical analysis part, I only use the results from the second round and generate an additional filter for subjects performing level-∞ thinking.

[12]In fact, I ask the subjects in the final questionnaire (only in sessions 2015 and 2016) whether they have played the GTN game before and roughly 37.3% state that they knew the game already. In comparison, only 1.2% stated that they have played a BR game before. See Table 1.5 for details.

[13]I use the first round results of Nagel (1995) which generated a mean of 36.73. The winning number in Nagel's study would thus have been $36.73\frac{2}{3} = 24.49$.

1.4.2.3 Noisy Bank Run Treatment

The noise associated with the signal about the fundamental is essential to global games theory as it generates *strategic uncertainty*, i.e., uncertainty about the behavior of other players in equilibrium (Morris and Shin, 2001). Understanding global games requires an understanding of how an equilibrium depends on the uncertainty of a player about other players' payoffs. But, as shown in section 1.4.2.2, beliefs about other players' payoffs are not sufficient. One has to take the beliefs about the beliefs of other players, and further higher order beliefs, into account. The introduction of the noise term in the global games approach eliminates the problem of multiple equilibria that we would have if economic fundamentals were common knowledge and agents would perfectly know each others payoff functions, such as in D&D. This offers a way to investigate the value of public information in the context of coordination problems, e.g., when "[f]inancial markets apparently 'overreact' to announcements from central bankers that merely state the obvious" (Morris and Shin, 2001, p. 5). From a central point of view there is an apparent trade-off between having multiple equilibria and providing less accurate information.

In this study, I am able to manipulate the accuracy of the information that subjects receive. For this I do not add any additional treatment but slightly change my BR treatment to study the effect of the size of the noise term. Instead of the range $[-0.1, 0.1]$ that defines the noise term ϵ in the 'normal' BR game I increase the range of the error term in the 'noisy' treatment to $[-0.3, 0.3]$. Vives (2014) states that agents receiving a less precise private information react more sensitive to bad signals. Hence, the larger the variation of the noise term the higher the required signal in order to prevent panic-based bank runs.

1.4.3 Theoretical Predictions

Theoretical predictions of optimal thresholds are derived similarly to Heinemann et al. (2004) and Klos and Sträter (2013) as lined out in Section 1.4.1. Table 1.3 presents the global games optimal thresholds, θ^*, that agents should use to decide on early or late withdrawal. Thresholds depend on the size of noise, ϵ, as well as on the risk aversion, denoted as α, of the individual. Furthermore, since subjects in the experiment receive signals that only have limited discrete accurateness there are two ways to compute the optimal thresholds: (1) discrete and (2) continuous. The discrete derivation limits signal and noise precision in the estimation to two decimal points. This means that there are only 191 different signals θ in the range from 1.20 to 3.10 available (and 21 noise terms ϵ in the range from -0.10 to +0.10). This leads to the problem that there is not a unique threshold in the discrete derivation but rather a range of signals that would represent optimal thresholds.

INSERT TABLE 1.3 AROUND HERE.

The influence of risk aversion, α, is taken into account assuming a power utility function of the form $u(c) = \frac{x^{1-\alpha}-1}{1-\alpha}$ with an initial wealth of 1. For the noisy signal with high risk aversion, subjects should withdraw early for any signal received, i.e., the optimal threshold θ^* is above the range of signals. This is denoted with W.

For example, a risk neutral individual in the normal BR treatment (small noise term) should use a threshold of $\theta^* = 2.6822$. For any signal below that threshold she should withdraw her deposits early and wait otherwise. For discrete input parameters the optimal threshold extends to an interval of $\theta^* \in [2.69, 2.87]$. For signals within this interval she would be indifferent between early and late withdrawal. As expected, the higher the risk aversion the higher is the optimal threshold. However, an increase in the noise term increases the threshold level only for individuals with a sufficiently large risk aversion. For risk loving individuals an increase in noise decreases θ^*.

1.4.4 Experimental Implementation

The experiment is implemented as a classroom experiment of a mandatory course on 'Banking' in the Bachelor of Arts program in Banking & Finance at the University of Zurich. Subjects are students of the course that have to participate in the experiment as a mandatory homework assignment that is part of their course assessment.

The experiment has been played in three consecutive cohorts in March 2014, March 2015, and April 2016. Before the students participate in the experiment they receive extensive training in banking theory in general and in the theory behind bank runs with a focus on the model of D&D in particular. Using sophisticated subjects (in the sense of knowledgeable in the theory of bank runs) is an attempt to simulate the behavior of institutional investors.

In every session, subjects have a pre-announced time frame of 24 hours to participate in the experiment. Students were informed about the conditions to participate in the experiment at the beginning of the course (8 weeks before the experiment). To ensure that a large fraction of the students participate they are granted five exam points (out of a total of 120) if they finish all treatments within the time frame.[14] The experiment is implemented as a browser game such that students can participate using their own computer with any modern web browser. Instructions are given in the form of text and video (see Appendix A.1 for transcripts).

[14]Participation rate is very high with 97.8% in 2014, 98.6% in 2015, and 95.5% in 2016.

At the beginning of the experiment, subjects are randomly assigned to one of six (eight) treatments as lined out in Figure 1.2. Table 1.4 lists the realized random assignments of the students to the different treatment orders.

INSERT TABLE 1.4 AROUND HERE.

A coordination game like the BR game in general requires players to participate in the experiment simultaneously. However, since I use students that participate in the experiment as part of a homework assignment, they may play at any time in a fixed time frame. I resolve this simultaneity issue by using decisions that I recorded for the identical BR game in Hegglin (2011). For the simulation there are a total of 648 group decisions for any possible value of the fundamental value θ. At the beginning of a round in the BR treatment a participant is randomly assigned to one of these 648 groups and randomly replaces one of the six depositors in this group. In total there are thus 3,888 different observed withdrawal scenarios. The advantage of this simulation approach is that it is impossible to build a reputation. Furthermore, there is no end-of-game effect being played by any other player.

1.5 Empirical Analysis

In total, there are 555 valid observations from 580 subjects that participated in the experiment. I drop 12 observations of subjects that always either withdrew early or late since it is technically not possible to estimate a binary outcome variable model without variation. Furthermore, I exclude 13 observations of subjects for which the probability of withdrawal early increases in the signal.[15] Furthermore, for 22 subjects not all 20 decision situations were recorded due to technical reasons. Subjects were able to participate in the experiment on any device with an internet connection, even mobile phones that may experience connection problems. I assume that connection problems are randomly distributed among subjects and hence do not drop the correctly recorded decision situations from the sample.

Table 1.5 provides an overview on descriptive statistics. Panel A presents some overall subject characteristics. Since the experiment was played as part of a mandatory lecture in the Bachelor's program of Banking & Finance most students belong to this study program for which the 4th semester equals the most likely point of study progress to attend the course. The fraction of females approximates the overall fraction in the study program (roughly 23%).

INSERT TABLE 1.5 AROUND HERE.

[15]Results remain qualitatively the same but lose power if I do not exclude these 13 observations.

Individual risk preferences are measured using a lottery-based risk elicitation task based on Holt and Laury (2002). Subjects are presented with a list of 10 paired lotteries for which the preferred lottery, A (safe choices) or B (risky choices), has to be picked in every row. Payoffs in the lotteries remain constant, only the probabilities change. Moving down the list the expected payoff of the risky option increases more than in the safe lottery until in the last row option B strictly dominates A. Risk aversion is estimated by counting the number of safe choices. Subjects are either *risk averse* (> 4 safe choices), *risk loving* (< 4 safe choices), or *risk neutral* ($= 4$ safe choices). Charness et al. (2013) estimates that choosing four safe options is approximately the equivalent of a CRRA coefficient α in the range of $[-0.15, +0.15]$. I observe that the majority of individuals (50.6%) chooses exactly the risk neutral strategy, while 35.9% (13.5%) are in line with risk averse (loving) preferences.

The affective state and the emotion of fear are measured as described in section 1.4.2.1. On average more than 90% claim they are rather happy and only roughly 7% declare that they experience the emotion fear at the time of playing the experiment.

Both risk aversion as well as affective state and fearfulness are measured in the experiment after some treatments already have taken place. Treatments are expected to have impact on some but not all individual characteristics. For example, the fraction of female participants should not differ between the treatments. On the other hand, risk preferences should be affected if priming was successful. Table 1.6 provides a series of randomization and treatment comparison tests that are based on the variables and subsamples of Table 1.5. Figures in the table correspond to the respective p-value of the underlying comparison test. As an example: The null hypothesis that the fraction of females is equivalent in the boom treatment and the control treatment cannot be rejected (p-value of 0.971 using a Pearson χ^2-test). Hence, we cannot say that females are not randomly distributed between the two groups. However, the same test for the same two groups reveals that the fraction of risk loving individuals differs at a significance level of 10% (p-value of 0.060). There are significantly more risk averse individuals in the boom treatment (17.0%) than in the control treatment (9.7%). Analogously we observe that the fraction of risk loving subjects was lower in the bust treatment (11.8%) than in the boom treatment but the difference is not significant (see column "Boom vs Bust" in Table 1.6). The randomization check also shows that individuals that play the GTN treatment first experience the emotion fear to a higher extent (p-value of 0.079). I later control for the order of the treatments in the regression analysis.

Insert Table 1.6 around here.

Panel B of Table 1.5 presents descriptive statistics for the BR treatment. I measure a total of 11,042 individual decisions from 555 subjects. On average, the subjects receive a signal of $\overline{\theta} = 2.171$ with a standard deviation of $\sigma = 0.493$. Since the true fundamental state is randomly and independently sampled from an identical sample space (see Section 1.4) the average value does not vary strongly between the different treatments. An average depositor decides to withdraw early in 6.66 out of 20 decision situations and faces 2.29 bank runs during the experiment. A two-sample Wilcoxon rank-rum test reveals that individuals in the bust treatment have a higher probability to withdraw early than in the no priming or the bust treatment (p-values of 0.059 and 0.010 respectively).

1.5.1 Estimation of Most Likely Thresholds

The first analysis of the BR treatment is a test of the Theorem I of Goldstein and Pauzner (2005). According to the global games theory agents decide to run on the bank if they receive a signal below a unique threshold θ^* and wait until $t = 2$ otherwise. I investigate whether agents use a unique threshold by estimating "most likely thresholds" and measuring corresponding error rates of these thresholds. Similar to Klos and Sträter (2013), I use two different methods: a logit model and a simple-error method. I illustrate the estimation procedure of both methods in Figure 1.4. The left panel shows a logistic regression of the signal θ_i on the binary decision whether the depositor withdraws early (=1) or late (=0). The red solid line maps the signal into a probability of early withdrawal based on the observed withdrawals of a single individual from the sample. Effective decisions are marked in the graph by hollow points on the bottom (= late withdrawal) and on the top (= early withdrawal). Decision situations that resulted in a bank run are additionally marked with an asterisk next to the hollow point. To illustrate potential changes of the threshold over time I add two additional logistic regression curves for the first ten (dotted green line) and the last ten (dashed blue line) decision situations. Decision points are colored analogously. The most likely threshold is now defined as the value θ where the subject is exactly indifferent between withdrawing early or late, i.e., where the predicted probability of early (or late) withdrawal is exactly 50%. This value is marked on the logistic regression curve with a solid dot. In the example given the most likely threshold lies at $\theta^* = 1.89$. Measuring only the first ten observations the threshold in this example would be lower ($\theta^*_{p\leq 10} = 1.76$) than in the latter ten observations ($\theta^*_{p>10} = 2.01$).

INSERT FIGURE 1.4 AROUND HERE.

The other approach to estimate the most likely threshold is a simple error model as proposed by Klos and Sträter (2013). In this procedure one iteratively tests every possible value $\hat{\theta}$ in the range of the signals $[1.2, 3.1]$ and counts the number of false withdrawal decisions assuming that $\hat{\theta}$ is the threshold in use. The most likely threshold thus is where the error rate is the lowest. In most cases the optimal threshold would not be unique but rather lie in a range. I therefore approximate the most likely threshold as the middle point between the first and last signal θ that minimizes the error rate. In the example in Figure 1.4 the error rate is 5% for a $\hat{\theta} = 1.70$ as a minimum and $\hat{\theta} = 2.03$ as maximum. The middle point is thus $\theta^* = 1.865$.

The average of all logistic regression model thresholds is $\hat{\theta}^*_{log} = 1.869$ whereas the mean simple error model threshold is $\hat{\theta}^*_{sem} = 1.868$. Hence, the chosen threshold strategy differs strongly from the optimal threshold predicted by global games theory ($\theta^* = 2.682$ for a risk neutral agent in the regular BR treatment). This confirms the results by Cabrales et al. (2007) and Klos and Sträter (2013) who also find large deviations of observed versus predicted optimal strategies.

I find that 36.9% of all subjects (205 out of 555) employ a "strict" threshold strategy, i.e., they withdraw their money early if the signal is below a certain fixed value θ^*_i and withdraw late if the signal is above. Another 31.7% employ an "almost strict" threshold strategy, i.e., they only make one mistake if I were to assume that they use a fixed threshold value θ^*_i. This provides evidence for Theorem I of Goldstein and Pauzner (2005) that agents employ unique threshold strategies.

Strikingly, the estimated logit and simple error model thresholds in the bust and noisy treatments are significantly higher than in the control treatment (p-values of 0.057 and 0.006 based on Student t-tests). On the other hand, depositors in the boom treatment require a significantly lower signal in order to keep trust in the bank compared to depositors in the bust treatment. This is also illustrated in Figure 1.5 where the left panel shows the development of the estimated threshold values $\hat{\theta}$ in the BR game over time and for different treatment groups. Threshold values are again derived from logistic regression models of withdrawal decisions. For each estimation, all observations from a subsample of four periods are taken together. The top graph shows the effect of priming: while the estimated thresholds of subjects in the boom treatment are consistently low, the thresholds of the control and the bust treatment are higher in almost all cases. On average, thresholds tend to increase over time. This observation is in line with Heinemann et al. (2004) who find that repeated interactions allow agents to approach the game theoretic solution.

Insert Figure 1.5 around here.

In the right panel of Figure 1.5, estimation errors for the derived thresholds from the left panel are computed for the same treatment groups and periods. It is interesting to see that estimation errors decrease over time. This may be attributed to a learning effect. For example, overall estimation errors for thresholds in the bust treatment is below 8% in the last four periods compared to more than 17% in the first four periods.

The middle two graphs show the same analysis for the subject groups that either started the experiment with the GTN treatment or the BR treatment. Depositors that first played GTN consistently require a larger threshold. This is in line with the expectation that subjects that have been primed with a beauty contest tend to think more about the potential behavior of their peers and also generate higher order beliefs in the BR treatment. This difference in thresholds is confirmed in a t-test that rejects the null hypothesis of identical means at the 5% level of significance.

The final two graphs illustrate the effect of an increase of the noise term on the estimated threshold. This is also in line with theoretical predictions for risk averse individuals. The absolute difference in the thresholds of 0.07 between subjects in the control and the noisy treatment is significant at the 1% level.

Panel C of Table 1.5 provides descriptive statistics for the GTN treatment. The first line corresponds to a randomization check and confirms that GTN treatment allocation is randomly distributed among the priming treatments. The next six variables cover the picked numbers in the guess 2/3 stage in the first and second round. On average, subjects chose a number of 22.38 in the first round and 17.34 in the second round. This corresponds to $k = 3.895$ and $k = 3.935$ iterations in level-k thinking (k was capped at 11). Overall, 10.3% and 7.9% of all picked numbers correspond to level-∞ strategies. These observations are marked and controlled for in the regression analysis later on. Estimates are roughly identical in all but the first round of the bust treatment (guessed average of 19.8).

The last Panel D provides details on how much subjects enjoyed participating in the experiment and whether they would like to have more classroom experiments of this sort. Both variables show that intrinsic motivation of students is very high and that the experiment was a very popular way to learn theory in an applied manner. Payoff measured in ECU or Chocolate pralines (one praline per 6 ECU) is evenly distributed across all treatments.

1.5.2 Panel Regression Analysis

In a next step, I try to identify factors that drive the decision whether a subject withdraws early or late. Obviously, the signal should be the main explanatory variable with the highest economic significance. With respect to the additional treatments, I expect an increase (decrease) in the threshold in the boom (bust) treatment compared to the control treatment. This corresponds to a higher (lower) probability of early withdrawal in the boom (bust) treatment. Furthermore, subjects that were primed with a beauty contest are expected to achieve higher levels k when generating beliefs about the behavior of their peers and thus should exhibit an increased probability of early withdrawal (equivalent to a decreased estimated threshold). Finally, theory predicts that risk averse individuals that receive noisier signals have higher uncertainty about the range of signals other depositors receive. This increases the likelihood of early withdrawal near the threshold and is reflected in a higher threshold.

Table 1.7 presents the results of a panel logit regression. I use the signal together with other explanatory variables to estimate a random-intercept logistic model on the binary indicator variable of early withdrawal, i.e., $\text{logit}\{P(y_{it} = 1|\mathbf{X}_{it}, \zeta_i)\}$ where y_{it} is equal to 1 if depositor i decides to withdraw early in period t, $\mathbf{X}_{it}$ represents the matrix of regressors, and ζ_i is the random intercept of agent i.[16] The sample is the unbalanced panel data set of 555 individuals with a total of 11,042 decision situations. Observations are clustered at the subject level. Coefficients are displayed as conditional odds ratios (equals the exponentiated logit regression coefficients), i.e., values below (above) 1 reduce (increase) the conditional odds given an increase in the corresponding regressor.

Insert Table 1.7 around here.

The first model includes the signal (scaled by a factor of 100) and the period of the decision (integer value of 1–20). The odds ratios coefficient for the signal is $\exp(\beta_1) = 0.930$. This shows that the withdrawal decision is highly sensitive to changes in the signal: a ceteris paribus increase in the signal of +0.01 multiplies the conditional odds for a subject by 0.930. Expressed differently, in terms of percentage change in estimated odds, the conditional odds decrease 7.0%. An increase in the signal of +0.1 would lead to a multiplication of the conditional odds of $0.930^{10} = 0.4835$, i.e., a percentage change of 51.65%. The probability of early withdrawal depends positively on the period of the experiment. Per additional period in the game, the percentage change in estimated odds increases by 1.2%. This confirms that subjects come closer to the game theoretic solution over time and with more experience.

Subsequent regression models (2) to (10) test to what extent the withdrawal decision depends on treatment and subject variables. Model (2) tests whether subjects in the bust or boom treatment react differently from subjects in the control treatment (this excludes subjects in the noisy treatment). The results provide evidence that the bust treatment significantly increases the odds of early withdrawal whereas the boom treatment decreases the probability although the latter coefficient is not significant. Comparing just the two groups of the bust and boom treatment (see model (3)) reveals that subjects primed with a bust have a 47.2% percentage increase in odds to withdraw early.

[16] A much simpler analysis is regressing all explanatory variables directly on the estimated logit thresholds from section 1.5.1 using OLS. However, the disadvantage of this approach is the loss of time-varying variables, such as the period, and that regressors are harder to interpret. Results in terms of signs and significance nevertheless remain qualitatively the same. For details, see supplementary Table A-1 in the Appendix.

In models (4) to (6) I analyze the effect of level-k thinking. Individuals that first played the GTN treatment have a higher likelihood to take possible actions of peer players into account and might thus generate higher order beliefs. The more iterations k a subject performs when thinking about what other players believe what other players believe, etc., the higher should the optimal threshold be and thus the higher the likelihood for an early withdrawal. Regression results confirm this intuition. Model (4) shows a positive change in odds for subjects that played the GTN treatment first. In model (5) I add the integer estimate for the level k that subjects employed in the second round of the GTN treatment. This regressor is positive too but not significant. The reason for that may be that many students picked the number zero, which would correspond to a level $k = \infty$. In the analysis, these observations were capped at a value of $k = 11$. If I exclude these observations with a filter (see model (6), filter abbreviated by "L-∞") I find that the level k has a highly significant and economically meaningful impact on the probability to withdraw early. Per additional level k the conditional odds to withdraw early increase by 10.2%.

Model (7) uses an indicator variable for subjects that played the BR game with a larger noise term of $\epsilon \in [-0.3, 0.3]$ instead of $[-0.1, 0.1]$. Theory suggests that individuals should increase their withdrawal threshold. To test this empirically I compare subjects from the noise treatment with subjects from the control treatment (I filter all observations of the boom or bust priming treatments). The coefficient is positive as expected and significant at the 5% level. I find that increased uncertainty about both the individual private signal as well as the range of signals that other depositors might have received increases the odds ratio of early withdrawal by 47.4%.

Section 1.4.3 has shown the influence of risk aversion on the theoretical optimal threshold θ^*. The higher the risk aversion the higher the likelihood that a depositor decides to withdraw early. I elicit risk preferences in the final questionnaire after the experimental treatments. Model (8) of Table 1.7 presents the corresponding regression results. Interestingly, I do not find a positive but rather an insignificant negative influence of risk aversion.[17]

Dijk (2015) suggests that the emotion of fear might be a driving force for the probability of running on the bank. He also finds that women in particular react significantly stronger to fear induction. Cohn et al. (2015) also conclude that subjects primed with a bust treatment exhibit significantly higher levels of fear. They suggest that the emotion of

[17] A possible explanation for this puzzling result might be that the elicitation task in the questionnaire was not incentivized. Subjects were simply asked to choose between lotteries without any consequence for their final payoff. An improvement to measure risk preferences would be to endow subjects with a fixed amount of ECU that generates a return according to a randomly picked lottery from the decision table.

fear, in turn, might have an effect on the perception of risk. Lee and Andrade (2011), for example, study the impact of fearfulness on stock trading. They observe that incidental fear increases both the risk aversion of the subject as well as the expectation of higher risk aversion among peers through social projection, i.e., that subjects take their current affective state as representative for other subjects. Applied to this study this would imply that subjects primed with a bust scenario exhibit higher risk aversion and higher levels of fear. This should directly (through risk aversion) and indirectly (through adverse expectations about the behavior of others) increase the likelihood of an early withdrawal. Although I find a small insignificant correlation between fearfulness and the bust treatment (results not reported here), I do not find evidence that fearfulness has a significant effect on the decision to withdraw money early (see model (9)). This result holds if the variable fear is interacted with a gender dummy and if control variables for the boom and bust treatments are added. The same applies for the variable that measures affective state. It is possible that the bust priming in this experiment only has had a small effect to stir up the emotion of fear. A self-induced fear treatment as in Dijk (2015) might improve the effect of the priming.

Different from Kiss et al. (2014b) I do find that women are significantly less likely to panic and thus require a lower signal to decide to withdraw early (see model (10)). However, I also find that females state more often that they experience the emotion of fear when participating in the experiment. Nevertheless, if I interact the gender variable with fear in a regression model, females still have a lower probability to withdraw money early (results not reported).

The last regression model (11) combines all explanatory variables of the previous models. The sample consists of all treatments combined and only excludes individuals that chose a value of zero in the GTN game. The only effects that remains robust in the overall sample are the variables of the GTN treatment as well as gender. The last column provides corresponding marginal effects on the estimated odds ratios of model (11) for changes in corresponding explanatory variables. For the signal, the marginal effect shows a change of +0.01, for all indicator variables a change from 0 to 1 and all other variables a change from the first to the third quartile. The strongest effects in the combined full sample come from the noisy treatment, the GTN treatment and the gender variable.

1.6 Conclusion

Banks increase welfare by writing contracts that generate liquid deposits based on illiquid assets. This maturity transformation creates multiple equilibria: a good equilibrium that offers risk sharing for patient agents and a bad equilibrium in which patient agents lose trust and run on the bank. This multiple equilibria problem has been solved by global games theory which is based on the idea that every agent receives a noisy private signal about the true fundamental state of the bank. Using this signal every agent can infer the optimal action and employs a threshold strategy: for signals above (below) a certain level the depositor stays with the bank (runs on the bank).

In this paper I use a simple experimental model of the global games theory and investigate factors that may influence the threshold level. My results contribute to the empirical analysis of global games models as well as to the understanding of determinants of banking crises on a micro-data level. I find evidence that depositors in my model use threshold strategies when deciding whether they want to withdraw early or late. An increase in risk aversion through a priming treatment positively influences the threshold level and raises the probability of a bank run. This may trigger a self-reinforcing feedback loop in which higher risk aversion leads to more bank runs which in turn increase risk aversion even further.

I find that subjects that do not only take their expectation about the behavior of other depositors into account but also their belief about the beliefs of other depositors, or even higher order beliefs, are more prone to produce panic-based runs. Strikingly, the more rational agents are and the closer they approach the game theoretic predictions the more likely bank runs become.

Finally, I find that larger uncertainty about the true fundamental state of the economy also increases the probability of bank runs. This contributes to the discussion of disclosure quality in the banking industry. More accurate public information decreases the likelihood of panic-based bank runs.

1.7 Figures

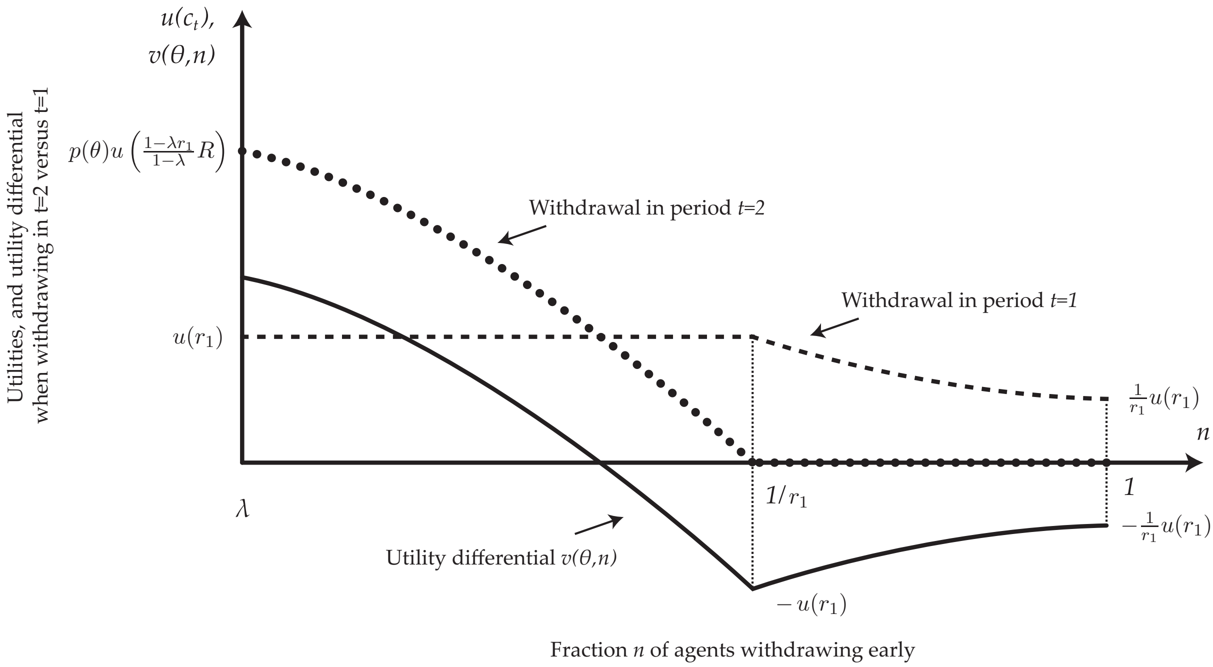


Figure 1.1

Utility Differential of a Late Withdrawal. This figure illustrates the utilities of early and late withdrawal and its differential. We see that utility from early withdrawal is constant as long as the bank has not declared bankruptcy and decreases with a higher fraction of individuals to withdraw in period 1 towards $u(r_1)/r_1$. The utility from late withdrawal is highest when all patient agents decide to withdraw late and decreases with a higher fraction of early withdrawals towards 0. Early withdrawal yields the same return as long as the bank is not bankrupt. Once the bank has gone bankrupt, utility from early withdrawal diminishes with a higher fraction of early withdrawers. Source: based on Goldstein and Pauzner (2005, p. 1305).

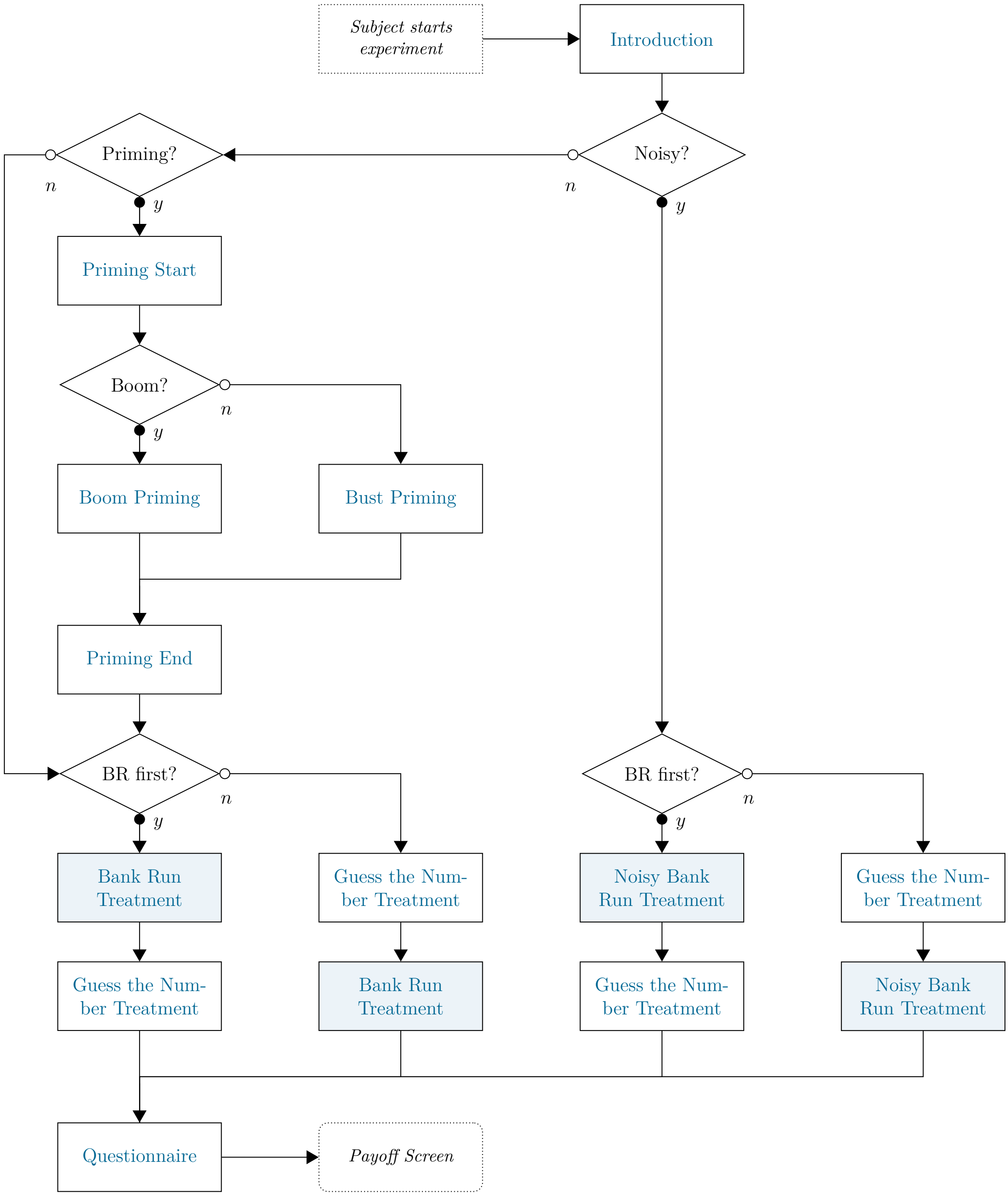


Figure 1.2

Experiment Treatment Flowchart. This figure illustrates the path through which subjects are directed throughout the experiment. Decision node ”Noisy?” with the ”Noisy Bank Run Treatment” was added in the sessions 2015 and 2016. Decision node “BR first?” tests whether the Bank Run treatment is played before the Guess the Number treatment.

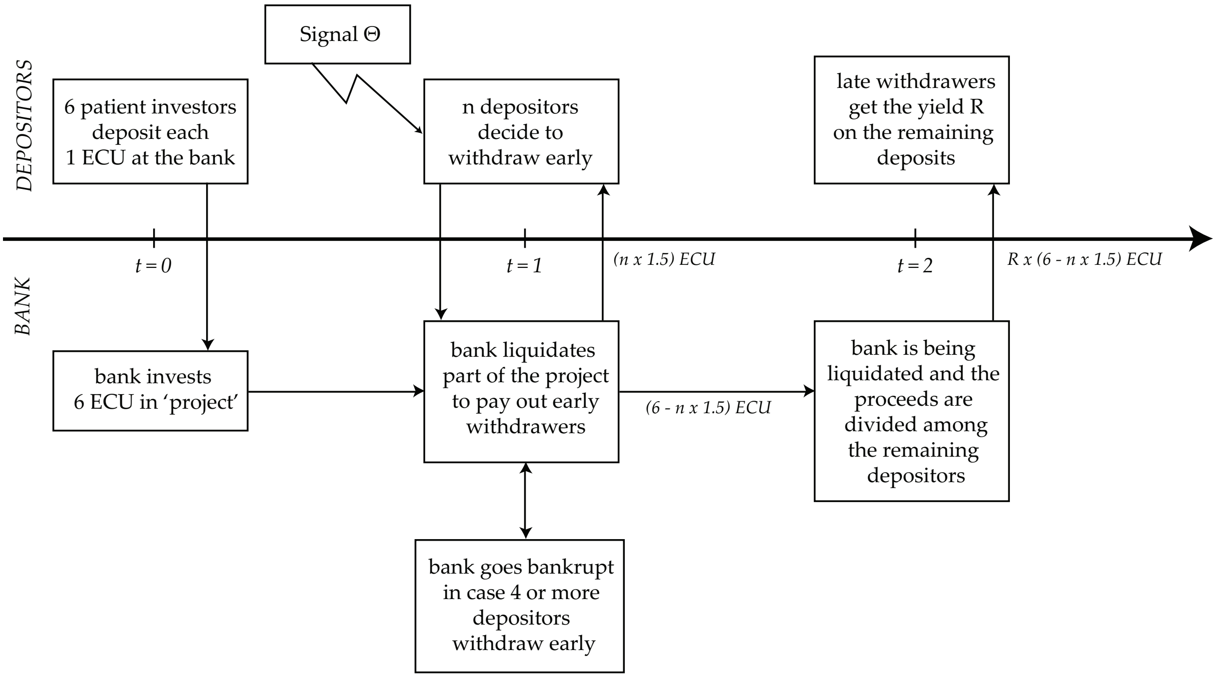


Figure 1.3

Timeline Bank Run Treatment. This figure depicts the timeline of the bank run treatment. At time $t = 0$ subjects are randomly assigned to a group of six investors. From these six investors five are observations of an earlier study of the experiment (see Hegglin (2011)) and thus simulated. Each investor invests 1 ECU at the bank. At the start of period $t = 1$ each investor receives a private signal θ with noise ϵ and decides whether to withdraw the investment or wait until period $t = 2$. If four or more investors withdraw early we have the situation of a bank run and the bank declares bankruptcy. In a bankruptcy case only four of all early withdrawing depositors are paid out. If there are five or six early withdrawing depositors nature decides which investors receive the promised repayment. If there is no bank run in $t = 1$ the bank liquidates what remained invested and distributes the proceedings equally among all late withdrawers. Source: based on Klos and Sträter (2013, p. 9).

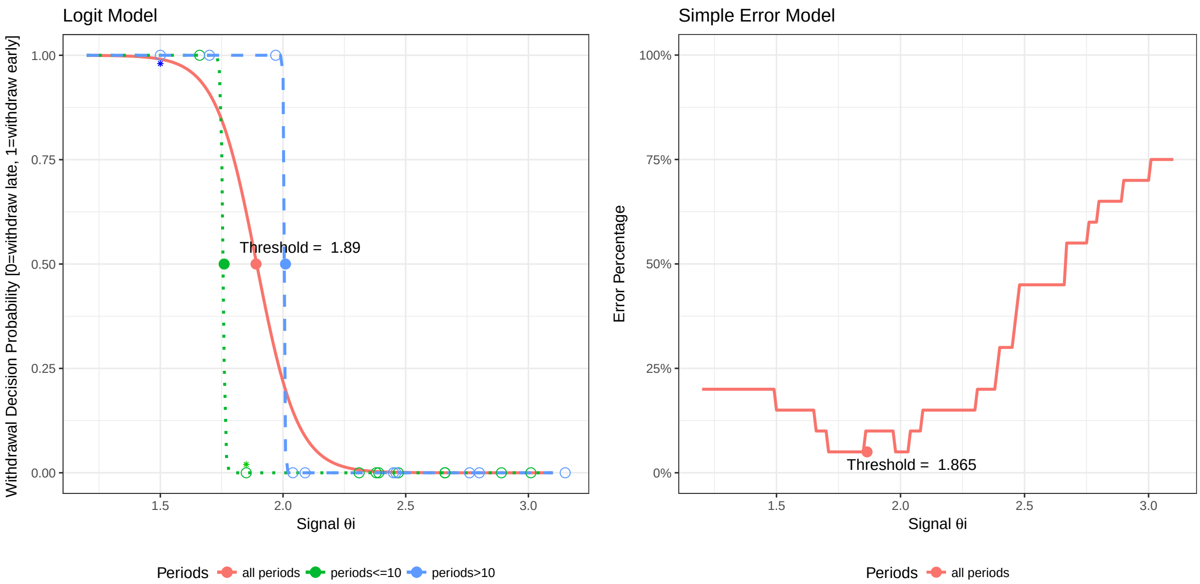


Figure 1.4

Logit and Simple-Error Model for Early Withdrawal Decision. This figure depicts the estimation of the most likely threshold chosen by a sample subject in the bank run treatment. The left panel shows a logit regression with the binary outcome variable withdraw early (=1) or withdraw late (=0) that is explained solely by the signal θ_i. The red solid line estimates the withdrawal probability over all 20 periods while the blue dashed (green dotted) curve estimate the withdrawal for the first ten (last ten) periods. Any decision is depicted by a hollow point on the bottom (for late withdrawal) or the top (for early withdrawal). Any withdrawal decision that resulted in a bank run is marked with an additional colored asterisk (blue for the first ten periods, green for the last ten periods). The most likely threshold is the value of θ where the subject is exactly indifferent between withdrawing early or late, i.e., where the predicted probability of early (or late) withdrawal is exactly 50%. On the right panel I depict the estimation of the most likely threshold using a simple error model similar to Klos and Sträter (2013) where I estimate the fraction of errors that I would observe for any given $\hat{\theta}$. I approximate the most likely threshold as the middle point between the first and last signal θ that minimizes the error rate.

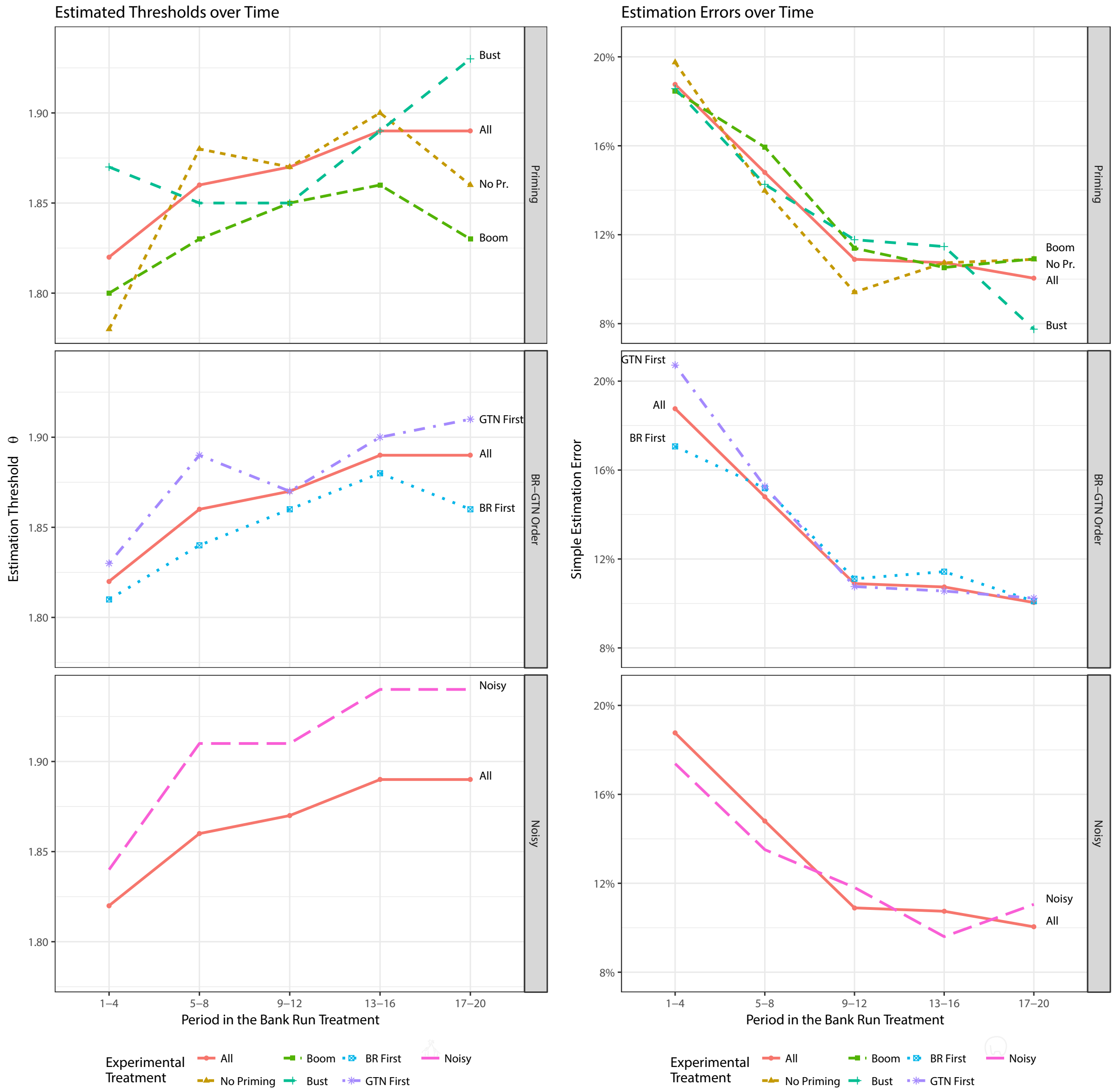


Figure 1.5

Threshold Estimation over Time. The left panel of this figure shows the development of the estimated threshold values $\hat{\theta}$ in the Bank Run game over time and for different treatment groups. Thresholds are derived from logistic regression models of withdrawal decisions (0 = withdraw late, 1 = withdraw early) on signals θ. For each estimation observations from a subsample within four periods are taken together. In the right panel estimation errors for the derived thresholds from the left panel are computed for the same treatment groups and periods.

1.8 Tables

Table 1.1

Ex Post Payoffs in the Bank Run Model. This table shows the general theoretical (Panel A) and the experimentally modelled (Panel B) ex post payments to agents depending on size of n, i.e., agents that decide to withdraw in $t = 1$. In Panel A, n represents a fraction of early withdrawers ($n \in [\lambda, 1]$), whereas in Panel B, n equals an integer number of agents withdrawing early ($n \in [0, 6]$). The payment r_1 is the promised refund of the bank to early withdrawers (only paid in full if the bank remains solvent) and R is the realized return of the investment project. Source: based on Goldstein and Pauzner (2005, p. 1299).

Panel A: General Theoretical Ex Post Payoffs

Withdrawal	*early* ($t = 1$)	*late* ($t = 2$)
no bank run ($n < 1/r_1$)	r_1	$\begin{cases} \frac{1-nr_1}{1-n}R & : \; p(\theta) \\ 0 & : \; 1 - p(\theta) \end{cases}$
bank run ($n \geq 1/r_1$)	$\begin{cases} r_1 & : \; \frac{1}{nr_1} \\ 0 & : \; (1 - \frac{1}{nr_1}) \end{cases}$	0

Panel B: Modelled Ex Post Payoffs in the Experiment

Withdrawal	*early* ($t = 1$)	*late* ($t = 2$)
no bank run ($n < 4$)	$r_1 = 1.5$	$R(6 - n \times 1.5)$
bank run ($n \geq 4$)	$\begin{cases} r_1 = 1.5 & : \; 4/n \\ 0 & : \; (1 - 4/n) \end{cases}$	0

Table 1.2

Payoff Table in the Decision Stage of the Bank Run Treatment. This is the payoff table being presented to investors in the decision stage before they have to decide whether they want to withdraw their investment early. As an example we have the depicted the case of $\theta = 2$. Source: based on Klos and Sträter (2013, Online-Appendix, p. 13).

		Period 1			Period 2		
Number of early withdrawers (withdraw in t=1)	Number of late withdrawers (withdraw in t=2)	Number of satisfied early withdrawers	Number of dissatisfied early withdrawers	Individual expected payment	Number of satisfied late withdrawers	Number of dissatisfied late withdrawers	Individual expected payment
0	6	-	-	-	6	0	2.00
1	5	1	0	1.50	5	0	1.80
2	4	2	0	1.50	4	0	1.50
3	3	3	0	1.50	3	0	1.00
4	2	4	0	1.50	0	2	0.00
5	1	4	1	1.50 or 0	0	1	0.00
6	0	4	2	1.50 or 0	-	-	-

Table 1.3

Theoretical Global Games Optimal Thresholds. This table lists the global games optimal thresholds, θ^*, that agents should use in the experiment when deciding to withdraw their deposit early or late. Thresholds depend on the size of noise, ϵ, as well as on the risk aversion, α, of the individual. Calculation of optimal thresholds is either discrete or continuous. Risk aversion is taken into account assuming a power utility function of the form $u(c) = \frac{x^{1-\alpha}-1}{1-\alpha}$ with an initial wealth of 1. For the noisy signal with high risk aversion, subjects should withdraw early for any signal received, i.e., the optimal threshold θ^* is above the range of signals. This is denoted with W.

		Risk aversion								
		Risk loving				Risk neutral				Risk averse
Noise		$\alpha = -0.20$	-0.15	-0.10	-0.05	0.00	+0.05	+0.10	+0.15	+0.20
$\epsilon \in [-0.1, 0.1]$	continuous	2.5950	2.6156	2.6368	2.6590	2.6822	2.7062	2.7312	2.7574	2.7846
	discrete	[2.60, 2.76]	[2.62, 2.79]	[2.64, 2.81]	[2.66, 2.84]	[2.69, 2.87]	[2.71, 2.90]	[2.74, 2.94]	[2.76, 3.02]	[2.79, 3.10]
$\epsilon \in [-0.3, 0.3]$	continuous	2.5286	2.5524	2.5794	2.6102	2.6466	2.6912	2.7504	2.8464	W
	discrete	[2.53, 2.60]	[2.56, 2.63]	[2.58, 2.67]	[2.62, 2.72]	[2.65, 2.79]	[2.70, 2.95]	[2.76, 3.10]	[2.85, 3.10]	[W, W]

Table 1.4

Number of Subjects per Session and Treatment. This table illustrates the number of subjects that had randomly been assigned to one of six (eight) possible different treatment orders in Session 1 in March 2014, Session 2 in March 2015, and Session 3 in April 2016. In a first step, the participants are assigned to either a *Boom*, a *Bust*, or to a *No Priming* treatment. In a second step, they either play the *Bank Run* or the *Guess the Number* treatment first. The *Noisy Bank Run* treatment has only been implemented as of 2015 and without priming of a boom or bust treatment. In this treatment the regular *Bank Run* treatment was replaced with a *Noisy Bank Run* treatment where the error term ϵ has a range of $[-0.3, 0.3]$ instead of $[-0.1, 0.1]$.

			2014	**2015**	**2016**	**Total**
No Priming	Bank Run	GTN	27	24	25	**76**
Boom			31	26	22	**79**
Bust			26	30	20	**76**
No Priming	GTN	Bank Run	31	30	17	**78**
Boom			29	22	29	**80**
Bust			33	25	19	**77**
No Priming	Noisy Bank Run	GTN	-	21	24	**45**
	GTN	Noisy Bank Run	-	25	19	**44**
			162	**203**	**157**	**555**

Table 1.5

Descriptive Statistics. This table provides descriptive statistics of characteristics and behavior of the subjects in the experiment. Data covers all 555 subjects. Subsamples are split in columns in either I) the three priming treatments "No Priming" (NP), "Boom", "Bust", and the "Noisy" treatment (all mutually exclusive), or II) the group that starts with the "Bank Run" or the "Guess the Number" treatment first. Data types of the variables are given in the second column, whereby *B* denotes *binary*, *C continuous*, and *D discrete* or *categorical* variables. Binary variables are described in the subsamples by absolute and relative frequency, continuous variables by their mean and standard deviation, and discrete variables by their mean and median value. Variables in Panel A include an indicator variable for *females* (=1 if female), *age* measured in years, students studying in the *Bachelor of Arts* in either *Banking & Finance* or *Business Administration* in the *3rd/4th* or the *5th/6th* semester. Subjects are either *risk loving* (< 4 safe choices in the questionnaire), *risk averse* (> 4 safe choices) or *risk neutral* (= 4 safe choices). *Fearfulness* and *Affective State* are discrete numbers in the ranges $[1 = \text{not at all}, 7 = \text{very strongly}]$ and $[1 = \text{very unhappy}, 9 = \text{very happy}]$ respectively. Variable *Dislike Chocolate* counts the individuals that answered that they rather dislike chocolate (score of 3 or less on a range from 1-6). Panel B provides details on the Bank Run treatment. The first row gives a count of the total observed decision situations. Variable *Fundamental* θ describes the average of the sampled θ in the experiment. The count of early withdrawals is provided in *#Early WD* (out of 20 decisions). Analogously, *#Bank Runs* counts the occurrences of bank runs in the 20 periods. *Logit Threshold* and *SEM Threshold* denote the individually most likely chosen threshold using a logit or simple error model. *Strict TS* is a binary variable whether the behavior of the subject can be described perfectly by a single strict threshold. *Know BR* is an indicator variable whether subjects already knew the BR treatment (only part of sessions 2015 and 2016). Variables in Panel C are an indicator variable whether subjects started with the GTN treatment, subjects' guessed numbers of 2/3 in the first (1) and second (2) attempt (*GTN est #1/#2*) as well as the corresponding level k for these guessed numbers (*Level-k est #1/#2*). *Level-*∞ is an indicator variable equal to 1 if the subject chose 0 as her best guess in the first and second round. *Know GTN* is an indicator variable whether subjects already knew the GTN treatment (only part of sessions 2015 and 2016). Panel D gives overall experiment details. The first variable, *Play again* measures whether subjects would like to see more similar classroom experiments (on a scale 1 = not at all to 6 = very much). *Exp Liking* shows how much the subjects enjoyed participating in the experiment (same scale). *Rev ECU* and *Rev Pralines* describe the respective payoffs in experimental currency unit and pralines.

		Overall Descriptive Statistics								I) Priming / Noisy Treatment								II) Start with			
		N	Min	Mean	SD	p25	Med	p75	Max	NP		Boom		Bust		Noisy		Bank Run		GTN	
Panel A: Subject Characteristics																					
Participants		555								154		159		153		89		279		276	
Females	*B*	550	0	0.240	0.427	0	0	0	1	37	24.0%	38	23.9%	38	24.8%	19	21.3%	71	25.4%	61	22.1%
Age	*C*	545	19.0	22.46	2.66	21.0	22.0	23.0	44.0	22.8	2.8	22.3	1.8	22.3	2.5	22.4	3.6	22.5	2.6	22.4	2.7
BA in B&F	*B*	555	0	0.631	0.483	0	1	1	1	93	60.4%	104	65.4%	95	62.1%	58	65.2%	173	62.0%	177	64.1%
BA in BusAdm	*B*	555	0	0.211	0.408	0	0	0	1	33	21.4%	35	22.0%	30	19.6%	19	21.3%	60	21.5%	57	20.7%
in 3/4 Semester	*B*	555	0	0.690	0.463	0	1	1	1	108	70.1%	109	68.6%	103	67.3%	63	70.8%	194	69.5%	189	68.5%
in 5/6 Semester	*B*	555	0	0.258	0.438	0	0	1	1	38	24.7%	41	25.8%	42	27.5%	22	24.7%	72	25.8%	71	25.7%
Risk loving	*B*	555	0	0.135	0.342	0	0	0	1	15	9.7%	27	17.0%	18	11.8%	15	16.9%	40	14.3%	35	12.7%
Risk neutral	*B*	555	0	0.506	0.500	0	1	1	1	87	56.5%	74	46.5%	75	49.0%	45	50.6%	147	52.7%	134	48.6%
Risk averse	*B*	555	0	0.359	0.480	0	0	1	1	52	33.8%	58	36.5%	60	39.2%	29	32.6%	92	33.0%	107	38.8%
Affective State	*D*	306	2	6.660	1.511	6	7	8	9	.	.	6.5	7	6.8	7	.	.	6.7	7	6.6	7
Fearfulness	*D*	312	1	2.010	1.241	1	2	3	7	.	.	1.9	2	2.1	2	.	.	1.9	2	2.1	2
Dislike Chocolate	*B*	555	0	0.162	0.369	0	0	0	1	23	14.9%	28	17.6%	31	20.3%	8	9.0%	41	14.7%	49	17.8%

Table to be continued

Table 1.5 – continued

		Overall Descriptive Statistics								I) Priming / Noisy Treatment								II) Start with			
		N	Min	Mean	SD	p25	Med	p75	Max	NP		Boom		Bust		Noisy		Bank Run		GTN	
Panel B: Bank Run Treatment																					
Total Decisions		11042								3068		3159		3047		1768		5490		5552	
Fundamental θ	*C*	555	1.30	2.171	0.493	1.73	2.21	2.60	2.99	2.17	0.50	2.16	0.49	2.15	0.50	2.18	0.48	2.15	0.50	2.16	0.49
#Early WD	*D*	555	1	6.658	2.608	5	7	8	16	6.58	6	6.38	6	7.12	7	6.52	6	6.54	7	6.79	7
#Bank Runs	*D*	555	0	2.286	1.462	1	2	3	7	2.32	2	2.36	2	2.35	2	1.98	2	2.29	2	2.28	2
Logit Threshold	*C*	555	1.42	1.869	0.202	1.73	1.88	1.99	2.77	1.85	0.20	1.84	0.21	1.89	0.21	1.92	0.17	1.85	0.19	1.89	0.21
SEM Threshold	*C*	555	1.35	1.868	0.204	1.73	1.89	2.00	2.64	1.85	0.19	1.84	0.22	1.90	0.21	1.91	0.18	1.85	0.20	1.89	0.20
Strict TS	*B*	555	0	0.369	0.483	0	0	1	1	59	38.3%	58	36.5%	52	34.0%	36	40.4%	89	31.9%	116	42.0%
Know BR	*B*	368	0	0.014	0.116	0	0	0	1	3	1.9%	1	0.6%	1	0.7%	0	0.0%	4	1.4%	1	0.4%
Panel C: Guess the Number Treatment																					
Start with GTN	*B*	555	0	0.503	0.500	0	1	1	1	78	50.6%	80	50.3%	77	50.3%	44	49.4%	279	100%	0	0.0%
GTN est #1	*C*	552	0.0	22.38	17.79	10.0	20.0	33.3	100	24.3	16.9	23.1	20.3	19.8	17.1	22.4	14.8	21.8	18.0	23.0	17.5
GTN est #2	*C*	553	0.0	17.34	11.85	10.2	16.0	22.4	80.0	17.3	11.0	18.3	13.9	16.3	11.4	17.5	9.6	17.5	11.3	17.2	12.4
Level-k est #1	*D*	555	0	3.895	3.247	2	3	4	11	3.5	3	3.9	3	4.4	3	3.7	3	4.0	3	3.8	3
Level-k est #2	*D*	555	0	3.935	2.648	2	3	4	11	3.9	3	3.9	3	4.1	3	3.7	3	3.9	3	4.0	3
Level-∞ #1	*B*	555	0	0.103	0.304	0	0	0	1	11	7.1%	19	11.9%	20	13.1%	7	7.9%	24	8.6%	33	12.0%
Level-∞ #2	*B*	555	0	0.079	0.270	0	0	0	1	12	7.8%	16	10.1%	11	7.2%	5	5.6%	20	7.2%	24	8.7%
Know GTN	*B*	370	0	0.381	0.486	0	0	1	1	35	22.7%	36	22.6%	39	25.5%	31	34.8%	61	21.9%	80	29.0%
Panel D: Overall Experiment Details																					
Play again	*D*	545	1	5.270	0.966	5	6	6	6	5.4	6	5.2	6	5.2	6	5.27	5	5.4	6	5.2	5
Exp Liking	*D*	544	1	5.184	0.887	5	5	6	6	5.2	5	5.1	5	5.2	5	5.35	5	5.3	5	5.1	5
Rev ECU	*C*	555	23.8	37.17	3.93	34.6	37.1	39.8	46.9	37.3	3.8	36.9	3.9	37.1	4.1	37.6	3.8	37.2	4.1	37.1	3.7
Rev Pralines	*D*	555	4	6.690	0.729	6	7	7	8	6.7	7	6.6	7	6.7	7	6.8	7	6.7	7	6.7	7

Table 1.6

Randomization Check and Treatment Effects. This table provides randomization and comparison tests for the variables described in Table 1.5. The second column describes the test that has been used to compare the different groups: The comparison tests are a Pearson χ^2-test for binary variables (denoted by χ^2), a Student's t-test of identical means for continuous variables (tt), and a two-sample Wilcoxon rank-sum (Mann-Whitney) test for categorical variables (rs). Results from the tests are presented as p-values. Values below $p < 0.1$ are given bold font weight.

		No Priming *vs*			Boom *vs*	BR *vs*
		Boom	Bust	Noisy	Bust	GTN first
Panel A: Subject Characteristics						
Females	χ^2	0.971	0.843	0.699	0.871	0.367
Age	tt	0.126	0.123	0.436	0.800	0.843
BA in B&F	χ^2	0.358	0.760	0.459	0.542	0.604
BA in BusAdm	χ^2	0.900	0.693	0.988	0.601	0.805
in 3/4 Semester	χ^2	0.762	0.595	0.914	0.815	0.788
in 5/6 Semester	χ^2	0.821	0.580	0.994	0.739	0.982
Risk loving	χ^2	**0.060**	0.567	0.104	0.190	0.568
Risk neutral	χ^2	**0.078**	0.190	0.371	0.661	0.330
Risk averse	χ^2	0.615	0.321	0.851	0.618	0.155
Affective State	rs	.	.	.	0.198	0.341
Fearfulness	rs	.	.	.	0.270	**0.079**
Dislike Chocolate	χ^2	0.522	0.220	0.181	0.550	0.328
Panel B: Bank Run Treatment						
Fundamental θ	tt	0.581	0.535	0.612	0.242	0.994
#Early WD	rs	0.372	**0.059**	0.839	**0.010**	0.426
#Bank Runs	rs	0.982	0.858	**0.066**	0.825	0.844
Logit Threshold	tt	0.693	**0.057**	**0.006**	**0.026**	**0.042**
SEM Threshold	tt	0.544	**0.048**	**0.009**	**0.014**	**0.031**
Strict TS	χ^2	0.737	0.430	0.742	0.645	**0.013**
Know BR	χ^2	0.302	0.317	**0.097**	0.982	0.173
Panel C: Guess the Number Treatment						
Start with GTN	χ^2	0.953	0.955	0.856	0.998	.
GTN est #1	tt	0.569	**0.021**	0.379	0.123	0.398
GTN est #2	tt	0.489	0.477	0.850	0.189	0.765
Level-k est #1	rs	0.308	**0.014**	0.442	0.226	0.699
Level-k est #2	rs	0.907	0.164	0.796	0.232	0.104
Level-∞ #1	χ^2	0.149	**0.085**	0.836	0.764	0.193
Level-∞ #2	χ^2	0.482	0.841	0.522	0.367	0.506
Know GTN	χ^2	0.986	0.511	0.869	0.497	**0.051**
Panel D: Overall Experiment Details						
Play again	rs	0.334	0.422	0.395	0.860	**0.026**
Exp Liking	rs	0.407	0.502	0.354	0.153	**0.015**
Rev ECU	tt	0.305	0.517	0.623	0.737	0.822
Rev Pralines	rs	0.328	0.581	0.750	0.689	0.964

Table 1.7

Panel Logit Regression Models on the Withdrawal Decision. This table presents panel logit regression results for eleven different random effects models to estimate the withdrawal behavior of subjects in the bank run treatment. The dependent variable is a binary indicator variable taking on the value of 1 if the subject withdraws early. *Signal* ($\times 10^2$) equals the signal θ_i scaled by a factor of 100, *Current Period* is an integer for the periods 1-20, *I(Boom)* is an indicator variable =1 if the subject went through the "boom treatment", *I(Bust)* analogously for the "bust treatment". *I(GTN first)* indicates whether the beauty contest is played before the bank run treatment (=1). *Level-k Estimate* is an integer value equal to the number of iterations the individual performed in the beauty contest, *I(Noisy Signals)* is an indicator variable =1 if the subject received noisy signals, *Risk aversion* is measured as ordinal value on a scale from 1 (risk loving) to 9 (risk averse), *Affective State* is an ordinal variable to indicate individual general affective state or happiness on a scale of 1 (very unhappy) to 9 (very happy), *Fearfulness* measures how much subjects experience the emotion fear on a scale from 1 (not at all) to 7 (a lot), *I(Female)* is an indicator variable =1 if the subject is female. Z-statistics are reported in parentheses. *** indicate statistical significance at $p < 0.01$, ** at $p < 0.05$, and * at $p < 0.1$.

		Estimations											*Mg. Eff.*
Withdraw in $t = 1$	HYP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	*(11)*
Signal ($\times 10^2$)	(–)	0.930***	0.930***	0.929***	0.930***	0.930***	0.930***	0.930***	0.930***	0.930***	0.930***	0.930***	*-7.0%*
		(-46.03)	(-42.28)	(-34.33)	(-46.05)	(-46.05)	(-44.26)	(-30.70)	(-45.91)	(-42.28)	(-45.78)	(-43.88)	
Current Period	(+)	1.012*	1.011	1.010	1.012*	1.012*	1.010	1.014	1.012**	1.011	1.012**	1.010	*11.0%*
		(1.90)	(1.61)	(1.16)	(1.91)	(1.90)	(1.50)	(1.52)	(1.97)	(1.61)	(1.99)	(1.63)	
I(Boom)	(–)		0.920									0.860	*-14.0%*
			(-0.52)									(-0.35)	
I(Bust)	(+)		1.317*	1.472**								1.055	*5.5%*
			(1.69)	(2.29)								(0.12)	
I(GTN first)	(+)				1.336**	1.331**	1.293**					1.327**	*32.7%*
					(2.42)	(2.39)	(2.09)					(2.29)	
Level-k Estimate	(+)					1.024	1.102***					1.081**	*16.9%*
						(1.02)	(2.70)					(2.10)	
I(Noisy Signals)	(+)							1.474**				1.342	*34.2%*
								(2.03)				(1.49)	
Risk aversion	(+)								0.942			0.993	*-0.7%*
									(-1.51)			(-0.18)	
Affective State	(–)									1.015		1.010	*7.6%*
										(0.66)		(0.20)	
Fearfulness	(+)									1.006		1.041	*8.3%*
										(0.11)		(0.54)	
I(Female)	(+/–)										0.762*	0.721**	*-27.9%*
											(-1.93)	(-2.25)	
Constant ($\times 10^3$)		646.3***	566.8***	705.0***	557.7***	504.3***	399.5***	462.2***	831.2***	566.4***	740.2***	479.4***	
		(42.15)	(37.59)	(30.89)	(41.33)	(39.41)	(36.91)	(27.85)	(37.38)	(37.72)	(41.78)	(31.68)	
Observations		11,042	9,274	6,206	11,042	11,042	10,169	4,836	11,002	9,274	10,942	10,029	
Number of id		555	466	312	555	555	511	243	553	466	550	504	
Treatment Filter		None	Noisy	No Pr.	None	None	L-∞	Priming	None	Noisy	None	L-∞	
Wald Test Statistic		2119	1788	1179	2121	2121	1959	944	2108	1788	2097	1927	
Prob > χ^2		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

2 Which Swiss Gnomes Attract Money? Efficiency and Reputation as Performance Drivers of Wealth Management Banks

Joint with Urs W. Birchler
Michael R. Reichenecker
Alexander F. Wagner

Of store of metals, which we pile,
And merrily greet: "Good cheer!" the while.
Well-meant the words, believe us, then!
We are the friends of all good men.

The Gnomes
Johann Wolfgang von Goethe

2.1 Introduction

Swiss Banks have often been compared to Gnomes, amassing and hoarding underground fortunes.[1] In this paper, we build on Goethe's description of the Gnomes as "always industrious everywhere," analyzing the link between Swiss wealth managers' industriousness and their performance. While Swiss wealth managers do work in relative secrecy like the Gnomes, they are required to disclose their "mining" performance, i.e., the yearly amount of net new money attracted from their customers. This makes Swiss private banking an ideal object of study.[2]

Private banks generate revenue by managing assets for wealthy private individuals. Two of the most important key figures in private banking are *assets under management* (AuM) and *net new money* (NNM). The more assets a private bank manages the larger is the basis on which the bank may generate fee and commission income. Assets under management may grow through two channels, either through capital gains or through the acquisition of new funds, i.e., by attracting new customers or by extending the 'share of wallet' of existing clients. Understanding the determinants of net new money thus is key to growth and performance in wealth management. The financial sector as a whole is an important contributor to GDP in many countries (State Secretariat for International Financial Matters SIF, 2014), with percentage contributions to GDP ranging from 3.6% (Germany), 6.6% (US), 8.6% (UK), 10.5% (Switzerland) to 11,2% (Singapore). While much research has been devoted to commercial and investment banking, the world of private banks and wealth management remains somewhat neglected and thus provides opportunities for research.

In this paper, we analyze the determinants of the creation of net new money for Swiss private banks. The Swiss private banking market provides an ideal setting for a study

[1] In the 1960s the "Gnomes of Zurich" were suspected of speculating against the British Pound. In popular belief, Gnomes are Goblin-like creatures mining and hoarding treasures underground, symbolizing the unbounded greed of wealth. They were first mentioned by Paracelsus and immortalized by Goethe in the famous scene on paper money in *Faust*. The full quotation may be found in the Appendix.

[2] The term "private banking" is often used as synonymous with wealth management, since originally, most Swiss wealth managers were in the form of so-called (fully liable) private banks (not denoting the opposite of public banks).

of this topic, even though (or precisely because) this market has been eyed critically for a long time. First, in international comparison, Switzerland has a high density of private banks and is a large market for cross-border wealth management. As of the end of 2014, Swiss banks managed approximately CHF 6.7 trillion assets, whereof 51.1 percent are assets from international customers (Swiss Bankers Association, 2015). Swiss private banks have an approximate market share of 25.0 percent in worldwide offshore wealth management. Section 2.2 presents a brief history of Swiss banking. Second, while one of the reasons for the lack of evidence on private banks is the secretive nature of these banks and the lack of data, Swiss regulation requires its banks[3] to report AuM, the composition of AuM as well as NNM in a standardized form under some conditions. Third, Swiss banks experienced a prolonged period of international political pressure as well as extensive cross-sectional variation related to fraudulent business practices and tax evasion. By exploiting variation in negative media coverage, this affords an opportunity to investigate the role of reputational risks in wealth management.

For our empirical analysis, we use a unique hand-collected data set of accounting reports for 87 private banks in Switzerland for the period of 2002 to 2014. Furthermore, we enlarge our data set with the accounts of 11 banks in the Principality of Liechtenstein. Private banking in Liechtenstein is very comparable to Switzerland due to its geographical proximity, identical currency, and similar regulation and reporting standards. In total, we study 98 private banks.

We begin by identifying banks that are comparatively more efficient in producing output, i.e. generation of income, given a vector of cost factors like wage costs, administrative costs, and depreciation while controlling for size. We measure *efficiency* through the standard figure cost-income ratio (CIR). Banks that achieve a lower (higher) CIR than implied by their input factors are more (less) skilled compared to other banks having similar input factors. We define the fixed effect component of abnormal CIR as the *skill* of a bank. The time-varying component of abnormal CIR captures unusual costs occurring in a year, for example, due to unusual depreciation (that occurs when a bank loses goodwill of customers).

In a second step, we then study the determinants of future net new money generation. We find that our *skill* factor has strong predictive power for future NNM attraction. Banks that have abnormally low CIR given their input factors are more successful in

[3]The Swiss Federal Banking Commission (SFBC) sets up the reporting standards for Swiss banks. Since the end of 2002, all banks in Switzerland that generate more than one-third of their revenues through commission and fee income over a moving average of three years have to give a structured report of assets under management and publish their net money flows. In what follows we define banks that fulfill the SFBC AuM reporting criteria as *private banks*, thus denoting them with the common term for banks that generate a larger portion of their income by wealth management services such as financial investment advisory or managing assets of wealthy customers.

generating net money flows in the future. We furthermore find that banks with negative media coverage experience large money outflows in the subsequent year. It is, in particular, relatively small banks that suffer most from negative media coverage. In our main specification, a bank below median size in terms of assets under management that experiences negative media coverage in one year has a 9.5 percentage point lower net new money growth (and, thus, often experiences net outflows) in the following year. Using estimates for the profits that banks make on assets under management, we calculate that this is roughly equivalent to a present value loss of 3.35 times the median annual net profit of a small bank. For a large bank, the present value of the damage of negative media coverage is 0.73 times the median annual net profit. Thus, reputational costs can be substantial.

We identify several other determinants of net new money growth. More employees (adjusted for the size of AuM) are associated with higher NNM growth, as are higher wages and bonuses for bank employees. Strikingly, returns on investment on funds managed for clients does not explain the variation in net new money growth of Swiss private banks.

Our paper is related to (1) the literature on reputational risk and trust in financial markets, (2) the literature on the role of relationships in banking, (3) the literature on private banking specifically, and (4) the literature on fund flows in the mutual funds industry.

First, the basis of wealth management is the clients' trust in the bank or, from the bank's perspective, reputation. Gennaioli et al. (2015) compare investors seeking professional investment advice to individuals seeing a doctor to get medical advice; investors may be anxious about investing because they have little knowledge of financial markets similar to a patient who does not know how to be cured. Investors in their model do not choose a portfolio manager because of past performance but rather because of trust and confidence. Our paper allows an empirical investigation of both aspects: the ability of a bank to attract new funds and customers as a function of trust and past investment performance.

The importance of generalized trust for stock market participation has been demonstrated by Guiso et al. (2008), and Giannetti and Wang (2016) document how household stock market participation decreases after the revelation of corporate fraud. There is a more limited empirical literature related to reputational risks in the financial industry. Most studies focus on stock market reactions of commercial banks after operational losses using event studies. Gillet et al. (2010) conduct an event study and compare stock price losses with the announcement of an operational loss. They find that operational losses resulting from internal fraud result in a greater loss of the stock price. They interpret the difference between the operational loss and the stock price loss as reputational damage.

Fiordelisi et al. (2013) try to elaborate on the determinants of reputational damage after operational losses in a similar setting. They find that the probability of reputational damage is increasing in firm size and profits and reduced by a higher level of capital and intangible assets. Sturm (2013) also investigates operational losses and their impact on reputational damage. He finds that stock prices react negatively both to press as well as settlement announcements of operational losses. Armour et al. (2017) document that a firm's "naming" as a wrongdoer by a UK regulator leads to negative stock price reactions that are substantially larger than the direct penalties imposed.

These studies consider studying the reactions of stock prices of publicly listed companies, and many focus on the announcement of operational damage. We focus on private banks that almost without exception are not listed on a stock exchange, and our interest lies in reputational damage occurring neither not operational losses, but through fraudulent practices associated with tax evasion.

Second, the term relationship banking often refers to a bank's ability to obtain lender-specific information over multiple interactions. A rich literature investigates the characteristics of the lender-borrower relationship. For extensive surveys, see Degryse et al. (2009) and Kysucky and Norden (2016). However, very little is known about the relationship of wealthy bank clients to their (private) banks. Our paper thus extends the existing literature by providing evidence on the relative importance of factors such as the reputation and performance of banks.

Third, there is only very limited empirical research on private banking.[4] Delaloye et al. (2012) conduct an event study to investigate the importance of banking secrecy for Swiss private banks. Other streams of literature focus on specific wealth management and banking topics. Foehn (2004) conducts a case study to determine the client value of private banking clients in Switzerland. Burgstaller and Cocca (2011) study the efficiency of private banking institutions in Switzerland and Liechtenstein. Cocca (2008) considers size effects and integrated business models in private banking in Switzerland and Liechtenstein. Horn and Rudolf (2012) investigate the determinants of service quality and its effects on private banks. Horn and Rudolf (2011) document that financial security affects customer loyalty more than service quality and they provide a first indication that banks outside Germany benefit more from their reputation for security.

Fourth, broadly speaking, our paper is also related to the mutual funds literature, which has investigated determinants of fund flows (e.g., Agarwal et al. (2009)). Kostovetsky (2016) demonstrates that following management-company ownership changes, a substantial decline of flows occurs. While there are some similarities, there are many differences between mutual funds and private banks, and a transfer of results obtained from

[4]Hens and Bachmann (2009), as well as Maude (2006), provide overviews of private banking in general.

one to the other is impossible. Kostovetsky (2016) cites a 2013 CFA Institute Edelman survey that found that 75% of investors believe the most important attribute for choosing an investment manager is trust (or ethics), whereas only 17% believe it is the ability to generate high returns.

The remainder of this paper is organized as follows. Section 2.2 presents some historical background of Swiss private banking. Section 2.3 provides the theoretical background of private banking for which section 2.4 presents the hypotheses and the empirical strategy. Section 2.5 describes the data. Section 2.6 presents the results, while section 2.7 concludes.

2.2 Swiss Private Banking: Historical Perspective

Switzerland was an early-bird in the Industrial Revolution,[5] but a laggard in banking. While local savings banks developed steadily from about 1830, the first decades of industrialization, until the 1860s, could mainly be financed from private savings. Yet, Swiss financial advisors had already offered their services internationally more than a century before the country even saw its first banks.

After the revocation of the Edict of Nantes in 1685,[6] numerous Huguenots (French protestants) found refuge in Switzerland, particularly in Geneva. In an attempt to rescue some of their funds left in France, they acquired financial practice and founded financial institutions. Most French banks, therefore, were of Swiss origin, among them the Banque de France (Luthy, 1963). Jean-Frédéric Perregaux, from Neuchâtel, financed the Napoleon Bonaparte's coup d'état of 1799; in exchange, he got the permission to create the Banque de France of which he became the first "regent" (Szramkiewicz, 1974).[7] Around the same time, two sons of Geneva – Jacques Necker (in 1777) and Albert Gallatin (in 1801) – became the equivalent of finance ministers in France and the US, respectively.

After the Versailles treaty, neutral Switzerland acquired the reputation of a financially safe haven. By the early twentieth century, both, the big banks and a number of mainly smaller full liability banks offered specialized service in wealth management. By that time, in several European countries, most notably France, increased taxation had replaced religious prosecution as a motive to move funds into Switzerland. Swiss banks were known for a strong secrecy culture (still based on civil law), and they openly advertised their assistance in tax protection abroad (Guex, 2000). During the First World War, foreign funds poured into Switzerland thanks to political neutrality, the stable currency, free movement of capital, mild taxation and, last but not least, bank secrecy (see Guex,

[5]Thanks, among else, to the ubiquity of water power.

[6]The revocation of the Edict ended religious tolerance and led to the emigration of many (protestant) Huguenots.

[7]The title Governor was only introduced a few years later.

2000). The strong position of Switzerland as a financial center was symbolized by the choice of Basel as the domicile of the Bank for International Settlements established in 1930.

In 1934, reacting to foreign pressure against its safe-haven policy, Switzerland made violations of bank secrecy a violation of the penal code in Article 47 of the Banking Act. A further feature of Swiss bank secrecy attractive for tax-shy international clients was the distinction between tax avoidance and tax fraud. Since only the latter is prosecuted under the penal code (avoidance only being punished by administrative fines), Swiss authorities cannot provide international legal assistance in tax avoidance cases.

Given this favorable framework, Swiss banks became leading wealth managers after the Second World War.[8] Swiss banking secrecy became a legend entering many books and movies. An initiative launched by the Social Democrats, calling, among else,[9] for the demise of bank secrecy, was rejected by a wide margin in 1984. In the late 1990s, Switzerland came under international pressure from groups representing, mainly Jewish, victims of the Holocaust (and their heirs), whose funds had become dormant in Swiss banks. In the following years, the issue was settled in several agreements; yet, Swiss banking secrecy has been somewhat tarnished since. About simultaneously to the 2007-2008 international Financial Crisis, Swiss banking took another hit: Pressure from several important countries led Switzerland to accept the so-called automatic exchange of information as an international standard, thereby putting an end to bank secrecy in matters of taxes for non-residents. As a consequence of the financial crisis and the shift of focus to tax compliant customers, assets under management stagnated from 2008-2013. They have started to grow again, and Swiss banks still are the leading wealth managers worldwide managing foreign funds of, roughly, USD 2.5 trillion.

2.3 Theoretical Background

To fix ideas and as a basis for our empirical hypotheses, we provide a simple formalization of a private bank's choice problem. A competitive bank offers advisory services on its assets under management. For each period t, the bank maximizes profit

$$P = A \cdot m - C, \tag{2.1}$$

where A denotes assets under management (AuM), m the gross profit margin, and C cost. The bank is a price taker in the AuM market, i.e., m is given exogenously. At the beginning of period $t+1$, the bank has a stock of assets under management, A_t. The

[8]Disclosure of funds under management and net new money only became mandatory as of 2003-2004.

[9]Another item was the introduction of government deposit insurance

bank can influence AuM growth and cost, however, via decision variables like the number of employees, wage per employee, and others. Decision variables have a lagged influence on AuM and cost. For example, a decision to increase staff only becomes effective in the following period. The maximization problem, based on Equation (2.1), therefore reads:

$$\max_{\mathbf{X}_t} P_{t+1} = \left(A_t + \Delta A_{t+1}\left(\mathbf{X}_t\right)\right) m_{t+1} - C_{t+1}\left(\mathbf{X}_t\right) \tag{2.2}$$

where $\mathbf{X}$ represents a vectors of decision variables affecting AuM and cost.

One difficulty of studying private banks' behavior in the data is that the overall variable of interest, P, is not observable: Some Swiss private banks do not disclose profit figures, while others publish profit figures post window-dressing. Assets under management (AuM) are, however, published and are comparable across banks, thus providing the basis for a performance measure. A complication arises here, too, in that an increase in AuM may either indicate true inflows of assets to be managed by the bank or just a higher value of assets already managed by the bank. In particular, swings in asset values may be due to the stock market, to changes in the interest rate and to changes in exchange rates, a factor that is quite important in a small country with its own currency.

We are interested in what banks can do to influence the actual in- and outflows. Thus, to exclude effects due to changes in valuation, we will use figures net of valuation effects, namely, *Net new money* (NNM). In our empirical analysis, we normalize NNM by the stock of assets under management.

Thus, the bank's maximization problem becomes:

$$\max_{\mathbf{X}_t} NNM_{t+1}\left(\mathbf{X}_t\right) m_{t+1} - C_{t+1}\left(\mathbf{X}_t\right) \tag{2.3}$$

In an *individual* bank's profit maximum, it equalizes the marginal benefit and marginal costs of the elements of $\mathbf{X}$. When regressing P (or NNM) on $\mathbf{X}$ for an individual bank, a non-zero coefficient on an element of $\mathbf{X}$ would suggest that the bank does not use the optimal amount of the respective input. In an empirical estimation of P (or NNM) *across* heterogeneous banks, though, one would not expect the coefficients of the elements of $\mathbf{X}$ to be zero. Banks using more of one particular input may be more profitable than those using less, even though individually they all operate at their optimum. Non-zero coefficients in our estimation may, therefore, reflect two different things: (i) a non-optimal factor mix at individual banks and/or (ii) profit-relevant heterogeneity of factor combinations across banks.

A bank's non-optimal factor mix in the sense of (i) may be due to the use of factors coming in discrete or even exogenous quantities. We will consider two such factors. The first is a variable we call "skill," a bank-specific parameter of cost efficiency, comparable to total factor productivity in a Cobb-Douglas production function. It reflects a bank's ability to optimally combine the input factors. A second profit-relevant variable is the reputation of a bank. The next section details our hypotheses regarding these factors and discusses their measurement.

2.4 Hypotheses and Empirical Strategy

We test two primary hypotheses as well as a number of secondary conjectures.

2.4.1 Efficiency and Skill

The first main hypothesis is that the performance of a bank in attracting new money depends positively on the bank management's "skill." Skill itself is unobservable. However, we can estimate, from the data, how efficiently a bank has been operating, relative to its peers, and this efficiency provides a measure of skill. Specifically, we expect that banks that are relatively more efficient than predicted by our model also perform better in attracting net new money. We use the *cost-income ratio*, the total operating expenses, and depreciation per unit of net operating profit, as an indication of a bank's efficiency. (This measure is also widely considered in practice.)

Concretely, as a first step, we estimate a regression model of the cost-income ratio using a set of input factors that describe the cost structure and the income structure of the bank. This allows us to identify both a bank-specific *abnormal efficiency* and a bank-year-specific *yearly abnormal efficiency* by predicting the idiosyncratic (time-varying) residuals.

Let $c(\mathbf{X}) = C/(A * m)$ denote the cost-income ratio (CIR). Splitting the cost-income ratio $c_{it}(\mathbf{X})$ of bank i in year t into a constant bank-specific component, $\bar{c}_i$, and the bank's yearly component e_{it} yields:

$$c_{it}(\mathbf{X}) = c(\mathbf{X}) + \bar{c}_i + e_{it}. \tag{2.4}$$

Our econometric methodology to measure $\bar{c}_i$, the bank-specific *abnormal efficiency* and the bank-year-specific *abnormal yearly efficiency*, e_{it}, as indicated in Equation (2.4) is to estimate a variance-components model of the cost-income ratio (CIR) over banks and time.

We thus estimate the following CIR_{it} model as an explicit version of Equation (2.4):

$$CIR_{it} = \alpha_0 + \alpha_1 x_{1it} + \cdots + \alpha_p x_{pit} + (\zeta_i + \epsilon_{it}) \tag{2.5}$$

where $\mathbf{X}_i$ contains capturing the (1) cost structure (e.g., the fraction of personnel expenses over total costs) and (2) income structure (e.g., the fraction of fee & commission income over total income), as well as the size of the bank. Denote the bank fixed effects by $\hat{\zeta}_i$ and the time-varying residuals by $\hat{\epsilon}_{it}$. Positive $\hat{\zeta}_i$ means that the bank has, on average, a higher CIR than predicted by our model. Banks with a positive (negative) $\hat{\zeta}_i$ are relatively less (more) skilled.

In a second step, we estimate net new money as:

$$NNM_{it} = \beta_0 + \beta_1\hat{\zeta}_i + \beta_2\hat{\epsilon}_{i,t-1} + \beta_3 z_{1i,t-1} + \cdots + \beta_q z_{qi,t-1} + \nu_{it} \tag{2.6}$$

where $\mathbf{Z}_i$ contains other variables that potentially explain the NNM_{it}. We expect β_1, the coefficient on the bank fixed effect, which indicates an abnormally inefficient bank, to be smaller than zero. In addition, we on purpose include the lagged year-specific residual. For β_2 we do not have a clear expectation. A positive value in a given year t may be the result of extraordinary investment in marketing (also after bad media coverage) and most likely produce higher money inflows in the coming year, while a positive value may also be the result of high costs due to depreciation of intangible assets such as value adjustments on client relationships and result in lower money inflows in the year after.

2.4.2 Reputation and Trust

The second main hypothesis is motivated by the idea, so far evidenced mostly anecdotally, that private banking is a relationship-driven business that is based on the central pillars confidentiality, security, trust, and the perceived level of client advisory service. The idea that client trust is a key source of revenue for "money doctors" is analyzed theoretically in Gennaioli et al. (2015). In recent years all these pillars have been seriously influenced by a series of negative outcomes; be it theft of bank clients' data, tax evasion scandals, or the abolishment of the banking secrecy. We hypothesize that banks incurring negative press coverage related to fraudulent business practices related to tax evasion find it harder to attract new money and may even experience money outflows. Even though, in the longer run, such reports may be endogenous to the bank's past decisions, the occurrence and timing of media reports are quite exogenous in the short run. We expect that the effect of negative media coverage is especially strong for smaller banks that are less diversified, and do not have access to other markets or other products to cover potential reputation damages.

2.4.3 Additional Conjectures

Third, we will consider a number of additional conjectures. Related to the creation of strong relationships with clients, we hypothesize that banks focussing on service characteristics such as a large number of bank employees per million in AuM, high incentives for employees as measured by wage costs per employee, and growth in the number of employees are positive performance drivers.

We also note that the goal of wealthy banking clients is to grow or at least maintain their wealth. This is why we expect that banks providing a high return on invested funds perform better in attracting new funds. We are especially interested in whether investment performance or reputation is more important for attracting new funds.

Moreover, we expect that banks offering asset management services and creating own funds profit from spill-over effects compared to banks focusing on relatively insensitive clients in management mandates. Finally, we expect that larger banks that potentially have access to various markets and other business segments attract more new funds.

2.5 Data

2.5.1 Sample

The empirical analysis relies on a unique hand-collected panel data set of private banks domiciled in Switzerland or the Principality of Liechtenstein (abbreviated as FL), drawing on data described in Birchler et al. (2015).

We combine Swiss with Liechtenstein banks since the two countries are very comparable in market structure due to geographical proximity, identical currency, and very similar regulation and reporting standards.

We start with all banks in Switzerland and Liechtenstein that use Swiss GAAP FER or the comparable Liechtenstein reporting standard. Then, we exclude banks that do not fulfill two additional criteria: (1) availability of audited data at least once in the sample period 2002-2014, and (2) reporting fee and commission income always above one-third of total revenues in a moving average of three years.[10] Criterion (1) leads to missing observations, mostly in the early years of the sample period. As for criterion (2), some banks do not fulfill the one-third rule only temporarily (because of strong performance in other bank-related areas). We only include banks focussing on financial and investment

[10]Per the rules of the Swiss Banking Authority, banks in Switzerland fulfilling this criterion have to hand in 'Table Q' to the supervisor (SFBC-Circ. 08/2, Rz 198a/b). Table Q lists six items: (i) assets in collective investment schemes managed by the bank, (ii) assets under discretionary asset management agreements, (iii) other managed assets, (iv) total managed assets (including double-counting), (v) double-counted items, and (vi) net new money inflow/outflow (including double counting)

advisory services for wealthy clients. This leaves us with a sample of 98 banks (87 banks in Switzerland and 11 banks headquartered in Liechtenstein). A sample attrition overview may be found in Table 2.1.

Insert Table 2.1 around here.

Insert Figure 2.1 around here.

For Switzerland, our sample of private banks corresponds to roughly one-third of all regulated banks and roughly one-fifth of all assets under management in Switzerland. We illustrate the composition of the sample in Figure 2.1. We have data of Swiss banks covering roughly CHF 4.7 trillion in assets under management. Out of this, our study does not include the very largest wealth managers, UBS and Credit Suisse, which together alone make up for about half of the overall assets. Like, for example, Julius Baer, they report under IFRS/US GAAP (instead of under the Swiss standard). Next, some banks cannot be included because they are true private banks that do not publish reports. A prime example of this category is Pictet (who published a report for the first time in 2015). (The 2012 assets under management here are estimated by Birchler et al. (2015).) The sample covered roughly accounts for CHF 1 trillion in assets. Figure 2.1 also illustrates the distribution of size in the sample of 2012. Two banks have around CHF 100 billion in assets under management, and the remainder is smaller, with the smallest banks somewhat below CHF 1 billion in assets under management. For Liechtenstein, almost two-thirds of all banks are in the sample.[11] Banks in Switzerland and Liechtenstein are required to publicly disclose their annual reports. (A challenge does arise, however, in that public disclosure does not necessarily mean that the reports are made available, for example, on a website. In some cases, as the data were built up over the years, the authors had to contact banks directly to obtain the reports.) Only 2 of the 98 banks in our sample are listed at a stock exchange.

Our sample period ranges from 2002 to 2014. We start in 2002 since this is when the Swiss Banking Authority implemented the new disclosure rules regarding assets under management and net new money. The panel is unbalanced due to changes in the availability of annual reports, due to mergers and acquisitions, or other status changes. During the sample period, 16 banks were dissolved, liquidated, or acquired by a competitor while six banks were newly founded or (re)started to publish their reports and were thus included newly(again) in the sample.

[11]For example, for the year 2014, there are 17 banks in Liechtenstein. Eleven banks fulfill our sample selection criteria.

2.5.2 Dependent Variables

Our main variables of interest are the cost-income ratio (CIR) and net new money (NNM), which equals the net amount of assets under management (AuM) of new and existing clients less the amount of assets withdrawn.

The *cost-income ratio* is total operating expenses and depreciation per unit of net operating profit. We include depreciation in the calculation of the cost-income ratio to account for the fact that banks can either buy or lease tangible assets. Consequently, leasing expenses are considered as operational costs and are incorporated in total administrative expenses. CIR is thus calculated as the sum of personnel expenses, material costs, and depreciation divided by the sum of interest income, fee & commission income, trading income, and other income.

Turning to net new money, the Swiss Federal Banking Commission (SFBC)[12] defines AuM to encompass all assets in self-managed collective investment instruments, assets from investors and clients in a wealth management contract. Additionally, AuM include assets in self-managed funds and assets with an investment advisory and/or investment service mandate.[13] "Custody-Assets" - assets that are held exclusively for safekeeping, custody or transaction purposes - are not considered as AuM as the bank does not provide any consultancy service.[14] The disclosure rules do not require separating inflows and outflows in the presentation of NNM figures.

Importantly, interest and dividend income, as well as market and currency movements on clients' assets, are excluded from this calculation. Thus, a positive NNM figure implies that the aggregated net asset inflow is higher than the aggregated amount that clients withdrew in the same period.

We standardize NNM figures by the average AuM holdings in the previous and current period to generate $NNM/AvAuM$, our main dependent variable.

2.5.3 Main Explanatory Variables

2.5.3.1 Cost-income Ratio (CIR) Regression Model

For the CIR regression model, we use variables that describe the business model and structural set-up of a bank in order to have high explanatory power for predicting the cost-income ratio for a bank for any given input factors. We use explanatory variables

[12] See SFBC Circular 24 (2002), Circular 38 (2006) and Circular 2 (2008).

[13] In particular, AuM include liabilities towards customers such as savings and deposits, time deposits, fiduciary deposits, and all portfolio assets. However, the statement is a non-exhaustive list and further details of inclusion have to be derived from the investment purpose.

[14] As reporting institutions are required to disclose the detailed criteria concerning the classification of custody assets, there could arise potential data limitations.

of three sources to describe the business model: (1) cost structure, (2) income structure, and (3) size.

We describe the cost structure by two different variables: (i) *personnel costs* and (ii) *depreciation costs* as a fraction of overall costs. Personnel costs are the sum of salaries, social security contributions, pension contributions, and other personnel-related expenses. Depreciation costs include depreciation of fixed assets and more importantly, intangible assets but exclude extraordinary value adjustments. We model the cost structure by dividing personnel costs and depreciation costs by overall costs which sum up personnel, material and depreciation costs.

Private banking costs are mainly driven by personnel costs which make up approximately 60% of all costs. The more a bank is focused on tailor-made wealth management (as, e.g. compared to interest-bearing activities or custodian business) the larger is the fraction of personnel costs in total costs, the larger are margins, and the lower is the cost to income ratio. A bank with high depreciation costs either has a high stock of tangible assets or extraordinarily writes off intangible assets due to bad circumstances. Balancing the two cost factors we expect that high personnel costs (and vice-versa low material and depreciation costs) reflect a lower cost-income ratio while high depreciation costs contrariwise reflect a higher cost-income ratio.

For the income structure, we distinguish two different income sources: (i) *fees and commissions* and (ii) *trading income*. Fees and commissions income is the net result from financial advisory and other services provided to clients. It captures the degree of specialization and is considered to proxy private banking knowledge. A focus on wealth management services leads to a higher fraction of income coming from fees and commissions. Trading income captures the net result from trading operations on foreign exchange and other securities trading. Operating revenue sums up fee & commission, interest, trading, and other income. We describe the income structure by dividing its components by operating revenue.

The last variable we use in the cost-income ratio regression is size. We expect that there are economies of scale in cost efficiency and hypothesize a smaller cost-income ratio for larger banks.

2.5.3.2 Net New Money Regression Model

For the NNM regression model we use the predicted level-1 and level-2 regression residuals $\hat{\zeta}_i$ and $\hat{\epsilon}_{i,t-1}$, that is, the bank-specific abnormal cost-income ratio and the abnormal bank-year-specific cost-income ratio, as shown in equation 2.5. An abnormally high value of $\hat{\zeta}_i$ indicates a bank with a constantly higher CIR than estimated by the model. An abnormally high value of $\hat{\epsilon}_{i,t-1}$ indicates a bank with a higher CIR than estimated by the model for the bank i in year $t-1$.

Furthermore, we introduce the *negative media* dummy, our second main variable of interest. Negative media is a binary indicator variable that equals one if a private bank received a negative media mention in a given year. In order to evaluate media coverage, we conduct a content analysis of the most influential and popular opinion-forming general and business newspapers in Switzerland.

For the media analysis, we assume that relevant news and bulletins affecting the Swiss financial center and the individual private bank are published and reported in the Swiss home media first and are afterward translated to international media agencies and broadcasted by international newswires. We conduct a content analysis using LexisNexis Academic International News and Wire database. For each year and institution, we search for articles that cover the bank in combination with reportings about tax scandals, banking secrecy, data theft or double taxation agreements. In a second step, we classify each article manually to have either positive or negative content. Further details concerning the use of specific search terms and the inspected newspapers and additional information on the media coverage in Switzerland and Germany can be found in the Appendix in Table B-1.

If financial security is a signal of stability demanded by affluent clients, we expect that banks with a higher *equity ratio* attract larger money inflows than banks with a high level of leverage. Equity ratio is the unweighted proportion of shareholders' equity to total assets and is a measure of the bank's capital strength. In recent years, high leverage has been tantamount to increased aggressiveness of the business model and managerial attitudes. Thus, a higher equity ratio may predict smaller net new money flows.

Since private banking is a pure service industry (Chase, 1981) predominantly determined by characteristics such as interaction quality (competence, investment proposal), service product quality (performance, product, and service range) and service environment quality (financial security and corporate identity).[15] Service quality per se is not directly measurable. We thus capture *service quality* indirectly through the total number of employees standardized by average AuM. We expect that the more employees a bank allocates to AuM, the better becomes the service quality. Two other ways to increase the service quality are to either increase the number of employees or to provide employees stronger incentives to attract new funds. We thus use the *Growth of Number of Employees* and the *Wage Costs per Employee* as further explanatory variables for service quality. Wage costs per employee is clearly a highly noisy measure of incentives. It is motivated by (a) the fact that the companies we study are in the same industry and should thus

[15]For example, Horn and Rudolf (2011) found that an improvement of service quality leads to higher growth of assets under management.

be competitive to each other with respect to pay practices and (b) the notion of basic economic theory that risk-averse agents receiving higher-powered incentives receive higher pay.

Finally, we assume that the goal of private banking clients is to grow or at least maintain their wealth. Clients are aware of a private bank's past performance to assess credibility and competence, similar to what clients of investment banks may do (Chemmanur and Fulghieri, 1994). Therefore, we posit that better past performance in the sense of greater client value created is positively associated with NNM growth.[16] We approximate *Client Value* by measuring the growth of AuM over one year, subtracting out the growth of the asset base through net clients' fund flows in the same period.

2.5.3.3 Descriptive Statistics

Because little is known so far about wealth management banks, we begin by offering some detail on the descriptive statistics of key variables of interest; see Tables 2.2 and 2.3.[17] Figure 2.2 shows the development over time of the two major dependent variables, the cost-income ratio (CIR) and net new money (NNM).

INSERT TABLES 2.2 AND 2.3 AROUND HERE.

INSERT FIGURE 2.2 AROUND HERE.

The banks in our sample exhibit an average CIR of 77.9% with a standard deviation of 22.0%. As seen in Figure 2.2, the average CIR has increased substantially over the years, with a structural break in 2008 (which makes it important to include year fixed effects in the analysis). This reflects challenges Swiss banks have experienced in the wake of increasing regulation, and increasing international competition (and, thus, declining revenues) as Swiss banking secrecy has come under attack.

In the cost structure, we observe that as expected the largest cost position belongs to personnel expenses with 60.1%, material costs equal approximately one third of the costs while depreciation plays a minor role (on average 6.8%) but fluctuates relatively strongly (standard deviation for depreciation cost is 6.9% while the much larger position of personnel expenses exhibits an only slightly larger standard deviation of 8.4%).

Also, as expected, the largest income source is from fees & commissions with almost two-thirds of operating revenues. Trading income represents 11.5% of operating revenues

[16]Note that a full test of this hypothesis should also consider the risks with which a given performance was achieved. However, this information is not available to us, clearly presenting a limitation of our analysis.

[17]We provide correlation matrices for all variables that are used in the regressions in the Appendix in Tables B-2 and B-3.

and thus plays a marginal role. Most private banks also offer Lombard credits and thus generate some interest income. Compared to credit institutions, the fraction (20.8%) remains relatively low. Other income plays a minor role for most private banks.

Describing the bank business model, we observe that 23.3% of the banks in our sample provide corporate finance or tax advisory services, 44.0% provide custodian and/or trading services to third-party independent asset managers, 37.4% provide financial and advisory services to institutional clients such as asset funds or pension funds, and 15.9% have specialized teams focussing on services specifically for single wealthy families. 14.2% of the banks have representative offices or branches in other countries within Europe (excluding Switzerland and Liechtenstein) and 25.1% in other countries outside Europe. Roughly one-seventh of all observations are from banks that are domiciled in Liechtenstein.

Turning to Table 2.3, we observe a large heterogeneity for net new money as well as assets under management. On average banks in our sample generated NNM of CHF 364.7 million (approximately USD 366.8 million at the end-of-2014 exchange rate) with a large range from a minimum of CHF -2,197.0 million to a maximum of CHF +6,485.7 million. Figures of assets under management are strongly positively skewed with a median of CHF 4,071.2 million and an average of CHF 13,674.4 million. The smallest bank-year observation in the sample displays CHF 339.2 million while the largest exhibits CHF 92,714.7 million. Our main variable of interest NNM/AvAuM is 2.7% on average with a considerably large standard deviation of 11.1%. The largest observed net outflow is -22.4%, while the highest net inflow equals +33.9%. As can be seen in Figure 2.2, the average NNM/AvAuM was around 5% in the early sample years, came down to around 0% from 2009 to 2013 and has recently increased again.

For roughly 28.9% of all bank-year observations, we identified press articles that match our search terms (we have a total of 4,380 articles for the 98 banks). 9.7% of all bank-year combinations exhibit negative media coverage.

Our control variables show that on average our banks exhibit an unweighted equity ratio of 16.6%, dedicate 0.024 bank employees per million in assets under management (i.e., on average a bank employee manages CHF 41.6 million AuM), pay an average salary of CHF 177,000 p.a., and have an average employee growth rate of 2.7%. The performance on funds invested equals +0.6% p.a. with a large standard deviation of 13.4%. On average, 5.8% of AuM are invested in funds created by the banks' own funds management division and 23.7% are assigned to dedicated management mandates.

2.6 Results

Table 2.4 provides the results from the cost-income ratio (CIR) estimation. We estimate five different fixed effects model specifications. The dependent variable is the cost-income ratio including depreciation costs. In the first four models we estimate CIR using different combinations of cost and income structures. Since both the fractions of personnel costs and depreciation costs as well as the fractions of fee and commissions income and trading income are by definition collinear respectively, we prefer one of the first four models (1-4) to avoid biased estimators. We employ Model (5) in a check to see whether results remain robust when combining all covariates. We employ year fixed effects and cluster standard errors on the bank level.

We find that banks with relatively high personnel costs as a fraction of total costs and low depreciation costs have a lower CIR. This makes sense as banks with a high fraction of their costs coming from personal costs tend to be banks strongly involved in private banking, and this is where margins are higher (and, therefore, the cost-income ratio is lower). Furthermore, banks that are specialized in wealth management and thus generate a larger fraction of income through fees and commissions income relative to trading income have a larger CIR. This is plausible, too, as the fees and commissions business is relatively cost-intensive.

Our models explain between 13 and 18 percent of inherent variability. The unexplained variability is separated into the two estimated level-1 and level-2 residuals, the fixed effect $\hat{\zeta}_i$ and the year-specific residual $\hat{\epsilon}_{i,t-1}$, for each cluster i. For model (1) we get a *between-cluster* standard deviations of $\hat{\theta} = 0.332$ for $\hat{\zeta}_i$ and a *within-cluster* standard deviation of $\hat{\psi} = 0.107$ for $\hat{\epsilon}_{i,t}$ (both mean values are 0 since $\mathbb{E}(\epsilon_{it}|\zeta_i) = 0$ and $\mathbb{E}(\zeta_i) = 0$ by definition). This shows that variation in the unexplained part of the cost-income ratio remains sizeable and that a considerable part can be explained in the variation across banks.

Insert Table 2.4 around here.

For the estimation of NNM, we use the estimated fixed effects and residuals of the CIR estimation. From Table 2.4, we use the first model specification. In what follows, the bank fixed effect from that regression is denoted abnormal CIR. The year-specific residual from that regression is denoted abnormal CIR year.[18]

In Table 2.5, we present the results of the random effects estimation.[19] We also employ year fixed effects and cluster standard errors on banks.

[18] In variations, we estimated NNM also with the other four CIR models. We find similar results. Table B-4 shows the estimation results for the richest CIR model specification. Most coefficients remain almost identical to Table 2.5.

[19] Table B-5 shows the results for a fixed-effects estimation dropping all cluster-level covariates.

Insert Table 2.5 around here.

We find strong support for both our primary hypotheses. First, banks that are relatively more efficient (displaying negative abnormal CIR) are also more efficient in attracting new money. The coefficient for abnormal CIR is, as hypothesized, negative and significant. In sum, we find strong evidence for the role of skill of a bank as a determinant of NNM growth.

We also find that the coefficient for the bank-year-specific efficiency is negative and in most specifications highly significant. Thus, extraordinary costs such as value adjustments on client relationships in one year also predict bad things for the future.

Our second main variable of interest, negative media coverage, shows a strong negative and highly significant impact on NNM. In model (1), we find that negative media leads to a change of −9.5 percentage points in NNM growth. This negative impact diminishes by +5.9 percentage points to −3.6 percentage points if the bank is large, i.e., with AuM above the median. These results for negative media coverage are in line with our hypotheses regarding the impact of reputational damage.

Negative media coverage has a significant economic effect on long-term profits. In Table 2.6, we derive the perpetuity loss a bank incurs with negative media coverage. Since large banks are able to cushion shocks more easily due to diversification, the effect is more pronounced for small banks. In expectation, a small bank loses CHF 7.1mn which equals 3.35 times net profit. Large banks, with AuM above the median, lose CHF 16.6m, the equivalent of 0.73 times net profit.

Next, we estimate several further models to expand our analysis to additional variables of interest. In model (2) we add the equity ratio as a regressor and find a slightly significant negative impact.[20]

In models (3) and (4) we test our hypotheses regarding the service characteristics of a bank. We find that private banks employing more relationship managers per million in AuM generate significantly more net new money. Similarly, banks expending more per employee (e.g., through incentives) achieve somewhat higher net new money, though the effect is not statistically significant. Pure growth of the number of employees is even less significantly positive.

Strikingly, we find that banks displaying higher returns on investment of funds managed for clients do not explain future net new money growth. The corresponding coefficient 'client value' in model (5) is insignificant. Overall, these results provide support

[20] Anecdotally, many bank representatives claim that a high equity ratio signals of financial stability and thereby attracts new clients. We find that a high equity ratio is not a positive driver for NNM. One interpretation is that a high equity ratio is a sign that a bank is pursuing a fairly conservative business model in general; thus, a high equity ratio may indicate a somewhat muted degree of aggressiveness in pursuing opportunities to attract NNM. On the other hand, a high equity ratio may be the result of high regulatory requirements to hold capital as a cushion for an already risky balance sheet structure.

for the theory, put forward in Gennaioli et al. (2015), that "money doctors" primarily benefit from the trust that clients put into them, but not from the actual performance they deliver.

In the last model (6) we combine all covariates and find that the coefficients remain robust and significant. Additionally, we add control variables testing whether a focus on the asset management and funds business, family offices as well as regional differences also explain future money flows. We find that banks that have a higher fraction of their funds in their own created funds attract more funds in the future. Furthermore, we observe that banks domiciled in Liechtenstein attract 7.1 percentage points more net new money per year than banks in Switzerland.

2.7 Conclusion

Private banking and wealth management have so far received scant attention in the literature, partially because of the difficulty of obtaining data. Attempting to fill this gap, this paper explores a unique panel dataset of the perhaps most developed wealth management industry worldwide, the Swiss and Liechtenstein private banking industry. Our panel allows us to provide a range of novel descriptive results regarding the cross-sectional and time-series variation of assets under management of Swiss and Liechtenstein private banks and their cost structure.

We obtain two key results. First, skill matters: those banks that operate more efficiently than expected from the inputs which they use also tend to be the ones who attract the most net new money. Second, reputation matters: banks appearing in negative media coverage (in particular in the context of tax evasion) experience sharply declining assets under management. The latter result, in particular, holds for small banks. Strikingly, flattering clients (measured by personnel expenditures) and upholding a high reputation seem to be still more important than performance in wealth management.

2.8 Figures

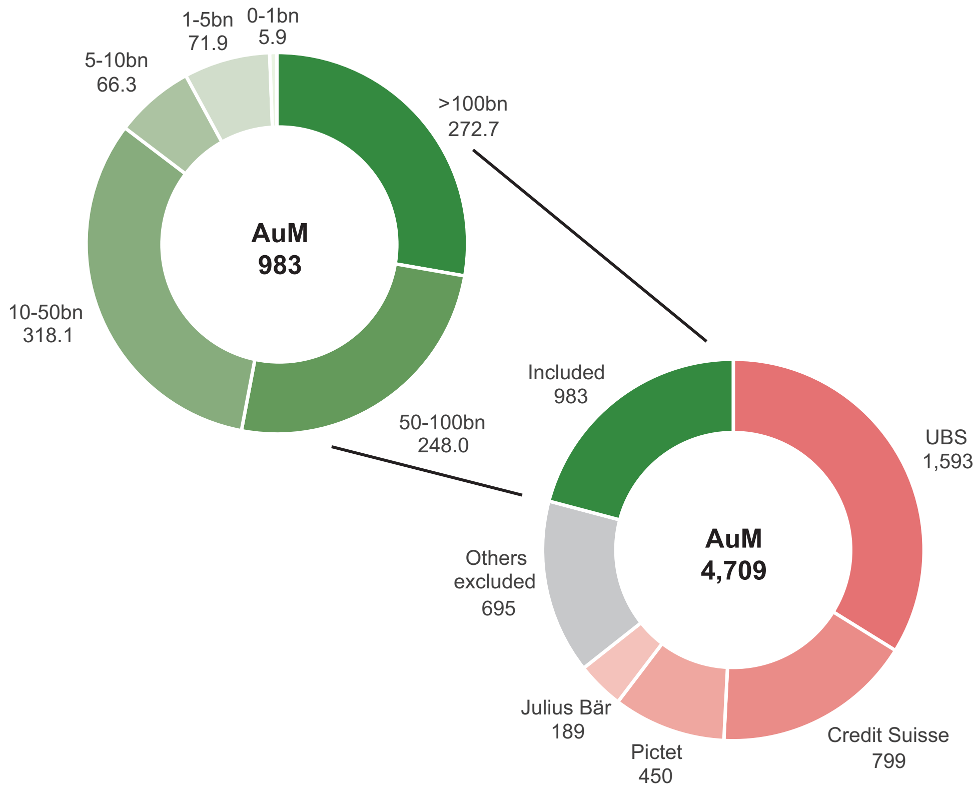


Figure 2.1

Coverage of Swiss Banks in the Sample. This figure illustrates the composition and coverage of our main sample of Swiss banks for one of the sample years, 2012. In that year, we have data of Swiss banks covering roughly CHF 4.7 trillion in assets under management. UBS, Credit Suisse, and Julius Baer report under IFRS/US GAAP instead of under the Swiss standard and are, therefore, not part of the sample. Some banks, such as Pictet, are not included because they do not publish reports. (Their 2012 assets under management reported here are estimated by Birchler et al. (2015).) After excluding these and related cases, the sample covered by this study roughly accounts for CHF 1 trillion in assets under management of Swiss banks in 2012.

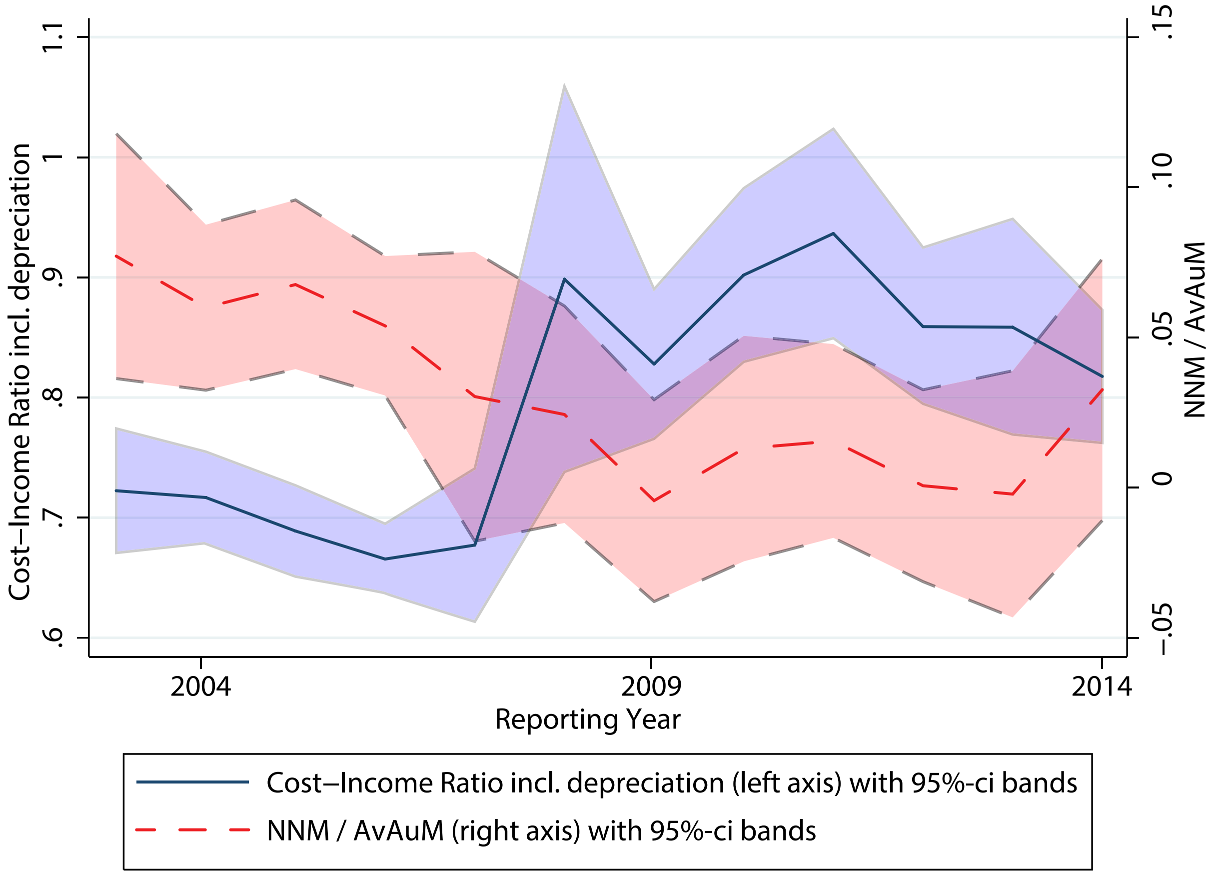


Figure 2.2

Time Series of Cost-Income Ratio and Net New Money. This figure shows the time series of the mean (and surrounding 95% interval) of the cost-income-ratio as solid blue line (left y-axis) and net new money scaled by average assets under management as dashed red line (right y-axis).

2.9 Tables

Table 2.1

Sample Attrition Table. This table shows a derivation of the sample used in this paper. We start with all banks in Switzerland and Liechtenstein that use Swiss GAAP FER or the comparable Liechtenstein reporting standard. Then, we exclude banks that do not fulfill two additional criteria: (1) availability of audited data at least once in the sample period 2002-2014, and (2) reporting at least one third of revenues from fee & commissions (f&c) income. Criterion (1) leads to missing observations mostly in the early years of the sample period. As for criterion (2) some banks do not fulfill the one third rule only temporarily (because of strong performance in other bank-related areas). Next, observations are dropped because of missing figures for our main variables AuM or NNM (this is especially true for banks in Liechtenstein where the publication of NNM is not mandatory). Depending on the regression model we use lagged or averaged variables. This may decrease the number of observations used in the regression models displayed in the estimation result tables.

	2002 – 2014	
	N	%
Total bank-year combinations	1,274	100%
excluded due to missing audited data (criterion 1)	436	34.2%
excluded due to temporary f&c income < 1/3 (criterion 2)	29	2.3%
Banks fulfilling criteria (1) & (2)	809	100.0%
missing Assets under Management (AuM) figures	*31*	*3.8%*
missing Net New Money (NNM) figures	*99*	*12.2%*
excluded due to missing any of AuM and/or NNM	100	12.4%
Bank-year observations	709	

Table 2.2

Descriptive Statistics I. This table presents descriptive statics for the dependent and independent variables of the CIR regressions. Observations are for 98 banks, sample period is 2002-2014. The *Cost-income ratio* is our main efficiency measure and is derived as *(Operational Costs + Depreciation) / Operational Revenue*. *Personnel Costs* are the sum of salaries, social security contributions, pension contributions and other personnel related expenses. *Material Costs* covers all operative costs that are not personnel related like occupancy expenses, IT costs, communication and marketing expenses, etc. *Depreciation Costs* include depreciation of fixed assets as well as intangible assets but exclude extraordinary value adjustments. *Total Costs* sum up personnel, material and depreciation costs. *Fee & Commissions Income* is the net result from commissions and fee income from financial advisory and other services provided to clients. *Interest Income* is the net result from interest activities. *Trading Income* is the net result from trading operations on foreign exchange and other securities trading. *Other Income* is the net result of any remaining income like results from the sale of financial investment, income from participations, or other ordinary income. *Operating Revenue* sums up fee & commission, interest, trading, and other income. *Bank domiciled in FL* is a dummy variable equal to 1 if the bank is headquartered in the Principality of Liechtenstein. *Services Corporate Clients* is a dummy variable equal to 1 if the bank provides services for corporate clients like corporate finance advisory, merger and acquisitions advisory, tax advisory. *Services IAMs* is a dummy variable equal to 1 if the bank provides custodian and / or trading services for third-party independent asset managers. *Services Institutional Clients* is a dummy variable equal to 1 if the bank provides advisory, trading, financial products services to institutional clients like asset funds or pension funds. *Services Family Offices* is a dummy variable equal to 1 if the bank has a specialized team that provides financial and advisory services specifically to single wealthy families. *Offices / Locations in Europe (excluding Switzerland)* is a dummy variable equal to 1 if the bank has representative offices or branches in Europe excluding Switzerland and Liechtenstein (FL). *Offices / Locations Worldwide (excluding Europe)* is a dummy variable equal to 1 if the bank has representative offices or branches in other countries excluding Europe. The data are winsorized at the 2.5th and 97.5th percentiles.

	Mean	Std. Dev	25th Percentile	Median	75th Percentile	Min	Max	Obs
EFFICIENCY MEASURE								
Cost-income ratio (incl. dep.)	0.779	0.220	0.624	0.742	0.880	0.443	1.526	709
COST STRUCTURE								
Personnel Costs / Tot. Costs	0.601	0.084	0.546	0.612	0.663	0.398	0.756	709
Depreciation / Tot. Costs	0.068	0.069	0.029	0.053	0.086	0.000	0.555	709
Material Costs / Tot. Costs	0.330	0.082	0.270	0.320	0.382	0.190	0.520	709
INCOME STRUCTURE								
Fee&Com. Income / Op. Rev.	0.634	0.135	0.529	0.647	0.744	0.312	0.874	709
Trading Income / Op. Rev.	0.115	0.060	0.080	0.108	0.141	-0.004	0.319	709
Interest Income / Op. Rev.	0.208	0.125	0.113	0.176	0.282	0.036	0.577	709
Other Income / Op. Rev.	0.044	0.073	0.002	0.015	0.052	-0.034	0.304	709
BANK BUSINESS MODEL								
Services Corporate Clients	0.233	0.423	0	0	0	0	1	709
Services IAMs	0.440	0.497	0	0	1	0	1	709
Services Institutional Clients	0.374	0.484	0	0	1	0	1	709
Services Family Offices	0.159	0.366	0	0	0	0	1	709
Offices/Loc. in Europe	0.142	0.350	0	0	0	0	1	709
Offices/Loc. Worldwide	0.251	0.434	0	0	1	0	1	709
Bank domiciled in FL	0.093	0.291	0	0	0	0	1	709

Table 2.3

Descriptive Statistics II. This table presents descriptive statics for the dependent and independent variables of the both the CIR and the NNM regressions. Observations are for 98 banks, the sample period is 2002-2014. *Net New Money* is the net Swiss franc amount of assets under management of new and existing clients less the amount of assets withdrawn. *Assets under Management* is the Swiss franc amount of assets under management in millions. *Net New Money / Average AuM* captures the aggregated net amount of assets under management acquired from new and existing clients standardized by the level of previous years AuM, NNM_t divided by the average of AuM_t and AuM_{t-1}. *Overall Media Coverage* is a dummy variable that equals to 1 if the bank was covered in the media in the corresponding year. *Negative Media Coverage* is a dummy variable equal to 1 if the bank exhibits negative media coverage in the corresponding year. The *Equity Ratio* is the ratio of shareholders' equity to unweighted total assets. *Service* captures the proportion of the number of total employees to total AuM expressed in million of Swiss francs. *Wage Costs per Employee* divides the sum of salaries and bonuses over average number of employees during the corresponding year. *Growth of Number of Employees* measures the net change in the number of employees during a reporting year. *Client Value* captures the growth of Assets under Management over one year's period less the growth of the asset base through net clients funds in the same period. *Own Funds/AvAuM* captures the ratio of AuM allocated in own funds while *Mgmt Mandates/AvAuM* measures the ratio of AuM in separated management mandates. The data are winsorized at the 2.5th and 97.5th percentiles.

	Mean	Std. Dev	25th Percentile	Median	75th Percentile	Min	Max	Obs
PERFORMANCE MEASURES								
Net New Money	364.7	1450.6	-119.8	51.0	392.2	-2197.0	6485.7	709
Assets under Management	13,674.4	22,488.4	1,546.9	4,071.2	11,993.0	339.2	92,714.7	709
Log(AuM)	8.457	1.474	7.345	8.312	3.392	5.830	11.437	709
Net New Money / AvAuM	0.027	0.111	-0.032	0.021	0.076	-0.224	0.339	709
MEDIA COVERAGE								
Overall Media Coverage	0.289	0.454	0	0	1	0	1	709
Negative Media Coverage	0.097	0.297	0	0	0	0	1	709
OTHER VARS								
Equity Ratio	0.166	0.101	0.093	0.136	0.214	0.048	0.488	709
Service	0.024	0.011	0.017	0.023	0.030	0.001	0.093	709
Wage Costs per Employee	0.177	0.047	0.146	0.170	0.199	0.079	0.428	709
Growth in No of Employees	0.027	0.129	-0.034	0.013	0.077	-0.262	0.434	652
Client Value	0.006	0.134	-0.063	0.022	0.076	-0.297	0.386	637
Own Funds / AvAuM	0.058	0.084	0	0.012	0.090	0	0.308	709
Mgmt Mandates / AvAuM	0.237	0.166	0.118	0.198	0.328	0.006	0.684	709

Table 2.4

Estimation of Cost-Income-Ratio. This table presents panel regression results for five different fixed effects models to estimate the cost-income ratio (CIR). The dependent variable is the cost-income ratio including depreciation costs. All regressors definitions are identical to the descriptive statistics Tables 2.2 and 2.3. Z-statistics based on robust standard errors clustered on banks are reported in parentheses. *** indicate statistical significance at $p < 0.01$, ** at $p < 0.05$, and * at $p < 0.1$.

				Models		
Cost-Income Ratio (incl. dep.)	Hyp	(1)	(2)	(3)	(4)	(5)
Personnel Costs / Total Costs	(−)	-1.475***	-1.461***			-1.102***
		(-7.30)	(-8.04)			(-6.16)
Depreciation Costs / Total Costs	(+)			1.701***	1.628***	0.774***
				(5.61)	(5.38)	(2.90)
Fee & Commissions Income / Op. Rev.	(+/−)	0.556***		0.623***		0.538***
		(4.35)		(5.02)		(3.70)
Trading Income / Op. Rev.	(+/−)		-0.470*		-0.541**	-0.194
			(-1.96)		(-2.17)	(-0.76)
Log(Assets under Management)	(−)	-0.205***	-0.191***	-0.231***	-0.216***	-0.212***
		(-4.87)	(-4.73)	(-5.46)	(-5.28)	(-5.21)
Constant		2.912***	3.216***	2.092***	2.451***	2.730***
		(8.11)	(9.22)	(6.08)	(7.18)	(7.60)
Year FE		Yes	Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	Yes	Yes
Observations		709	709	709	709	709
Number of Banks		98	98	98	98	98
R^2_{within}		0.58	0.55	0.55	0.51	0.60
$R^2_{between}$		0.10	0.09	0.07	0.06	0.09
$R^2_{overall}$		0.17	0.17	0.14	0.13	0.18

Table 2.5

Estimation of Net New Money / AuM. This table presents random effects panel regression results for six different models to estimate the performance of a private bank as measured by net new money flows. The dependent variable is the Net New Money scaled by AvAuM. All explanatory variables are lagged by one year. The bank-specific abnormal cost-income ratio (ζ_i) as well as the bank-year-specific cost-income ratio (ϵ_{it}) are predicted from model (1) in Table 2.4. All other regressors definitions are identical to the descriptive statics Tables 2.2 and 2.3. Z-statistics based on robust standard errors clustered on banks are reported in parentheses. *** indicate statistical significance at $p < 0.01$, ** at $p < 0.05$, and * at $p < 0.1$.

		Models					
Net New Money / AvAuM	Hyp	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal CIR (ζ_i)	(−)	-0.076***	-0.092***	-0.094***	-0.115***	-0.074***	-0.084**
		(-2.73)	(-2.99)	(-3.18)	(-3.52)	(-2.61)	(-2.44)
Abnormal CIR Year (ϵ_{it})	(+/−)	-0.114***	-0.112***	-0.135***	-0.120***	-0.099**	-0.113**
		(-2.70)	(-2.67)	(-3.21)	(-2.72)	(-2.07)	(-2.41)
Negative Media Coverage	(−)	-0.095***	-0.101***	-0.094***	-0.107***	-0.099***	-0.106***
		(-3.63)	(-3.69)	(-3.41)	(-3.47)	(-3.53)	(-3.68)
NegMedCov X [AuM > Med]	(+)	0.059**	0.067**	0.058**	0.074**	0.060**	0.075**
		(2.09)	(2.30)	(1.97)	(2.30)	(2.00)	(2.45)
AuM Above Median	(+)	0.036**	0.034*	0.053***	0.048***	0.041**	0.042**
		(2.13)	(1.96)	(3.15)	(2.87)	(2.42)	(2.52)
Equity Ratio	(+/−)		-0.123*		-0.207***		-0.213***
			(-1.79)		(-2.94)		(-3.04)
Service Quality	(+)			2.315***	1.818**		2.255***
				(2.72)	(2.20)		(2.71)
Wage Costs per Employee	(+)			0.201	0.210		0.285*
				(1.34)	(1.33)		(1.79)
Growth of Number of Emp.	(+)				0.041		0.025
					(1.18)		(0.73)
Client Value	(+)					0.028	0.013
						(0.64)	(0.30)
Own Funds / AvAuM	(+)						0.142**
							(2.13)
Mgmt Mandates / AvAuM	(−)						0.051
							(1.33)
Bank domiciled in FL	(+/−)						0.071***
							(3.16)
Constant		0.064***	0.091***	-0.037	-0.010	0.034***	-0.054
		(3.55)	(3.79)	(-0.80)	(-0.24)	(2.70)	(-1.18)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Observations		607	607	607	551	536	536
Number of Banks		96	96	96	92	92	92
R^2_{within}		0.13	0.13	0.17	0.17	0.13	0.17
$R^2_{between}$		0.02	0.07	0.02	0.07	0.02	0.13
$R^2_{overall}$		0.09	0.10	0.10	0.14	0.10	0.17

Table 2.6

Loss Due Negative Media Coverage. This table shows an approximation of the loss incurred due to negative media coverage separated by size. We distinguish small banks (Assets under Management below the median) from large banks (above median). A shock through negative media coverage reduces the AuM growth rate by 9.50 percentage points for small banks, and 3.60 percentage points for large banks. We estimate fees & commissions income by multiplying the AuM post media dummy with the median adjusted gross margins. Using a relatively conservative perpetuity yield of 15% we are able to estimate the loss incurred due to negative media coverage. Small banks lose CHF 7.1mn what equals 3.35 times the median net profit while large banks loose CHF 16.6mn what equals 0.73 times the median net profit.

	Small banks		Large banks	
	w/o shock	with shock	w/o shock	with shock
AuM pre Media Dummy [in mio]	1,510	1,510	10,796	10,796
AuM Shock: change in AuM growth	0%	-9.50%	0%	-3.60%
AuM post Media Dummy [in mio]	1,510	1,367	10,796	10,407
Adjusted Gross Margin on AuM [%]	0.74%	0.74%	0.64%	0.64%
Fees & Commission Income [in mio]	11.2	10.2	69.0	66.5
Present Value of FCI [perpetuity yield 15%]	74.9	67.8	460.1	443.5
Loss due to Neg Media Dummy [in mio]		7.1		16.6
Median Net Profit [in mio]		2.1		22.7
# Net Profits Lost due to Neg Media Dummy		3.35		0.73

3 The ECB's Three-Year Bank-Refinancing Operations and Eurozone Bank Equity

Joint with Jiri Woschitz

3.1 Introduction

As of October 2008, the European Central Bank (ECB) uses different types of unconventional monetary policy measures as a response to the financial and – later on – the European sovereign debt crisis. Among other measures, the ECB offers repeatedly supplementary repurchase agreements (repos) to Eurozone banks with durations exceeding those of conventional one-week and three-month repos. From 2008 to 2012 the ECB offers 20 six-month, four one-year, and two three-year operations in addition to the conventional operations.[1] Until today, the three-year operations have been the largest bank-refinancing operations between the ECB and Eurozone banks.

This paper studies the impact of these three-year central bank repos on stock prices of Eurozone banks. Under the efficient market hypothesis, abnormal returns on Eurozone bank stocks should reflect the market's opinion of actual values. Compared to other studies, this paper is narrow in the sense that we exclusively focus on the three-year operations and bank equity to distinguish between the effects in two ways. First, we differentiate between two "shocks" that the three-year repos entail. The first shock is the announcement of the extraordinarily long-dated duration of three years. The second shock is represented by the large liquidity uptake by banks in the aggregate.[2] Therefore, we separate the effects of the announcement from those of the cash settlements. The announcement and the large uptake in the first three-year transaction are expected to shock the stock market while the large uptake in the second operation – more than two

[1] Woschitz (2017) studies these operations in the context of bank rollover risks and provides a detailed overview of all such supplementary operations, which he denotes as "extraordinary LTROs".

[2] In standard three-month transactions roughly 100 to 300 banks bid for aggregate amounts between EUR 15 and 70 billion. In the two three-year operations, at least 800 counterparties bid for an aggregate amount of, in total, more than EUR 1,000 billion (these numbers are from Woschitz, 2017, Table 1).

months after the first cash settlement – should at this point be incorporated into the banks' stock prices.

Second, we analyze bank stock reactions in depth across Eurozone countries. Nyborg (2017) argues that the three-year operations served as an indirect bailout of financially weaker banks and sovereigns. Crosignani, Faria-e Castro, and Fonseca (2017) show that Portuguese banks use the liquidity uptake from the first three-year operation to buy high-yielding Portuguese short-term government debt. In the second three-year repo they receive even more liquidity by pledging these bonds as collateral with the ECB. This type of "collateral trade" suggests that the three-year funds flow from financially weak banks to financially weak sovereigns which is in line with Nyborg (2017).[3] Nyborg's argument, however, would also suggest that the three-year operations have higher positive abnormal effects on bank equity in financially weaker countries. Therefore, we examine the impact of the three-year repos separately for each of the 12 Eurozone countries in our sample.

Notice that relatively higher abnormal bank equity returns in weaker countries are not in line with the "moral suasion" argument (see, e.g., Battistini, Pagano, and Simonelli, 2014; De Marco and Macchiavelli, 2016; Reinhart and Sbrancia, 2015), claiming that banks are coaxed by the governments to use the liquidity uptake to purchase domestic sovereign debt. If a bank – as a profit maximizer – buys government debt because the government urges it but not out of its own accord, strictly speaking, it destroys equity value. Correspondingly, if the market thinks moral suasion is at work, the bank's equity price should fall.

The data for the event study is downloaded from Thomson Reuters Datastream. In our main setup, we estimate abnormal returns for 89 listed Eurozone banks across 12 different countries using a standard market model as described in MacKinlay (1997) and country-level total market return indices. Abnormal returns are then combined into cumulative abnormal returns over a variety of different event windows and averaged across banks within a country. To assess statistical significance, we use different test statistics (Boehmer, Musumeci, and Poulsen, 1991; Brown and Warner, 1980; Kolari and Pynnönen, 2010) which enable us to better understand the abnormal return correlation structure.[4]

[3]In this vein, Acharya and Steffen (2015) provide evidence that Eurozone bank risks in the period from 2007 to 2013 exhibit patterns similar to a large-scale bank carry trade behavior because bank equity returns load positively (negatively) on bond returns of peripheral countries (German government bond returns). The authors find that this carry trade behavior is stronger for banks with low capital ratios and high risk-weighted assets, which supports the risk-shifting hypothesis (see, e.g., Diamond and Rajan, 2011).

[4]As pointed out by Aït-Sahalia, Andritzky, Jobst, Nowak, and Tamirisa (2012), using event studies has a number of advantages. The estimation is relatively simple, gives an immediate response on a short-horizon estimate for the market reaction, and avoids specification issues in the underlying model. However, disadvantageous is that the estimated effects do not necessarily measure direct causality. Furthermore, there is an apparent trade-off between narrow and wide windows. Narrow windows exclude potential colluding effects but might miss potentially delayed or anticipated reactions of market par-

The main findings are as follows. We observe statistically significant cumulative abnormal returns, at the level of 10%, over different event windows of 4.0% in Italy up to 15.3% in Spain when we use the test statistic developed by Brown and Warner (1980). This test statistic essentially builds an equally-weighted portfolio across banks within a country and evaluates the statistical significance of these equally-weighted portfolio returns. In comparison, cumulative abnormal returns statistically different from zero in non-peripheral countries range from −4.9% in Austria to −3.1% in the Netherlands. Using the more conservative test statistic developed by Kolari and Pynnönen (2010), which explicitly controls for cross-correlation of bank stocks, leaves one cumulative abnormal return, 11.7% in Spain, in peripheral countries statistically significant at the level of 10%. However, cumulative abnormal returns of 4.0%, 6.3%, and 9.6% in Italy over different event windows have p-values of 11.3%, 11.4%, and 12.9%, respectively. The corresponding statistically significant cumulative abnormal returns for non-peripheral countries lie between −4.9% in Austria and 5.4% in Germany. Estimates of country-level liquidity uptake reveal that the largest and second-largest uptakes, on a country-level, were made by Spanish and Italian banks, respectively.[5] For instance, we estimate the liquidity uptake of Spanish banks to be more than four times larger than the one by German banks. This is in line with the argument that the three-year operations served as an indirect bailout for banks in financially weaker countries (Nyborg, 2017).

Similarly, over the first cash settlement (using the test statistic proposed by Brown and Warner, 1980), in peripheral countries statistically significant cumulative abnormal returns, at the 10% level, lie between 4.4% in Italy and 16.0% in Portugal across different windows. In non-peripheral countries, Belgium is the only country with at least one cumulative abnormal return (6.5%) statistically different from zero. Using the more conservative test statistic in the peripheral countries leaves one cumulative abnormal return, 2.3% in Spain, statistically different from zero at the level of 10%. One cumulative abnormal return, 16.0% in Portugal, however, has a p-value of 12.0%. Correspondingly for non-peripheral countries, this test statistic leaves only one cumulative abnormal return, 1.9% in Finland, statistically significant (at the 5% level). Crosignani et al. (2017) show that Portuguese banks ran "collateral trades" on high-yielding Portuguese sovereign bonds using the three-year liquidity uptake. The high abnormal returns on Portuguese banks' equity combined with Crosignani et al. (2017)'s finding provides, again, evidence for the indirect bailout argument made by Nyborg (2017).

ticipants. The latter we address by calculating cumulative abnormal returns over a variety of different windows.

[5]The data is collected from Bruegel (see Pisani-Ferry and Wolff, 2012) and the webpages of the Eurosystem's national central banks.

Overall, these findings provide evidence that banks in peripheral countries profit disproportionately more over the announcement and the first cash settlement of the three-year operations in terms of equity price increases than banks in non-peripheral countries.

Over the second cash settlement, we find – not surprisingly – mixed results. The large liquidity uptake in the first operation might have been unexpected by the market. The large uptake in the second operation – more than two months after the first operation – likely was not a surprise to the market anymore.

We do a variety of robustness checks along the lines of Nyborg (2017) which confirm these findings. First, we use equally-weighted bank stock returns per country instead of the bank stock returns themselves. Second, we replace each country-level market index by the "STOXX Europe 600". Also, third, we replace the equally-weighted portfolios or bank stock-level returns by country-level bank indices. The findings remain qualitatively the same.

Our paper relates to literature that examines the impact of unconventional monetary policy measures on the equity prices of banks. Close to our study, Nyborg (2017) investigates the influence of the announcement of the large-scale asset purchase programs (September 4, 2014) on bank equity across Eurozone countries. He finds that especially banks in peripheral Eurozone countries profit from positive abnormal equity returns. Our analysis distinguishes itself from that of Nyborg (2017) by assessing the three-year operations instead of the asset purchase program. Fiordelisi et al. (2014) analyze the effects of both conventional and unconventional policy actions on the interbank credit market, the stock market, and the banking sector. While conventional measures tend to be more effective on the interbank market, unconventional measures have a larger impact on the stock market. Ricci (2015) studies the impact of ECB announcements in general on a sample of 28 European banks from 2007 to 2013. She finds that unconventional measures have a stronger impact than conventional actions and that especially risky banks with low capitalization react most sensitively to policy interventions.

Other event studies investigate the impact of unconventional (and conventional) central bank measures in a broader spectrum. Aït-Sahalia et al. (2012) categorize several different policy actions in the US, UK, Eurozone, and Japan from 2007 to 2009 and examine their individual effects on interbank risk premia. They find that interest rate cuts and bank recapitalizations are strong drivers for positive market responses but do not find strong evidence that liquidity support relieved pressure on the interbank market. Lambert and Ueda (2014) determine the effect of unconventional central bank policies on announcement dates between 2000 and 2012 on changes in yield spreads and on bank stock returns in the US, Euro area, and the UK. Using one-year-ahead futures of the three-month Eurodollar and Euribor rates as measures of the surprise element of monetary policies (see Bernanke and Kuttner, 2005) for the US and the Euro area, respectively, they find no significant effect for bank stock returns in the US but a positive effect in the Euro area after September 2008. Haitsma, Unalmis, and de Haan (2016) test the reaction of stock markets to policies of the ECB from 1999 to 2015 and find that in particular unconventional monetary policy actions affect stock prices. Furthermore, they find evidence of a credit channel, especially in the crisis period, to which highly levered firms are most sensitive. Falagiarda and Reitz (2015) identify more than 50 unconventional monetary policy events by the ECB and investigate their effect on sovereign spreads of peripheral countries relative to Germany from 2008 to 2012. They find that the unconventional measures reduced long-term government bond yields in all peripheral countries except Greece whereby events in the period 2010 to 2012, the Securities Markets Programme, and the Outright Monetary Transactions had a strong impact.

Different methodologies are used to assess unconventional policy measures. Rigobon and Sack (2004) address the problem of endogeneity when estimating the impact of monetary policy on different asset prices and propose to use a heteroskedasticity estimator for variance increases. Kholodilin, Montagnoli, Napolitano, and Siliverstovs (2009) apply the heteroskedasticity approach by Rigobon and Sack (2004) and show that the monetary policy of the ECB has differential effects on sectoral stock markets in the Eurozone. Eser and Schwaab (2016) use a time series panel regression model to estimate the yield impact of the Securities Markets Programme in five Eurozone sovereign bond markets. The authors show that bond yield volatility and tail risk reduce on intervention days. Pelizzon, Subrahmanyam, Tomio, and Uno (2016) investigate the market liquidity depending on credit risk in the European sovereign debt markets using a vector autoregression setting. They argue that sovereign credit risk dynamically drives market liquidity. This link of market makers' liquidity provision to credit risk weakens with the three-year repo announcement in December 2011. Interestingly, their model estimates that the most likely structural break date is December 21, 2011, which represents the auction date of the first three-year transaction studied in this paper. Saka, Fuertes, and Kalotychou (2015) study Eurozone fragility by analyzing Draghi's famous "whatever it takes" speech. The authors use principal component and event study methodology to show that after the speech, the perceived default risk commonality has increased among peripheral and core Eurozone sovereigns.

Most event studies on monetary policy actions focus on the US. For example, Yin and Yang (2013) find that on the US market large and poorly capitalized banks as well as banks relying more on interbank liquidity react more strongly to unexpected interest rate changes. Bernanke and Kuttner (2005) use a technique proposed by Kuttner (2001) to distinguish expected from unexpected policy actions based on changes in Federal funds futures. They show that an unexpected 25bp cut in the Federal funds rate increases broad stock indices by 1%. Gagnon, Raskin, Remache, and Sack (2011) study large-scale asset purchases in the US and provide evidence that these led to long-lasting reductions in longer-term interest rates not only on securities bought in the purchase programs. Krishnamurthy and Vissing-Jorgensen (2011) apply an event study to evaluate the effect of the Fed's Quantitative Easing programs QE1 and QE2 on interest rates. They identify and separate different channels through which the bond purchase programs affect interest rates. Swanson (2011) studies the effect of Operation Twist in the context of QE2 on long-term interest rates. The author finds that the effects on longer-term treasury yields are about 15 basis points, while the effects on longer-term agency and corporate bonds are smaller. Glick and Leduc (2012) study large-scale asset purchases by the Federal Reserve and the Bank of England since 2008 and find that announcements about purchases lowered long-term interest rates through a signaling channel about future growth. Kontonikas, MacDonald, and Saggu (2013) examine US stock returns after changes in Federal funds futures between 1989 and 2012. They show that in contrast to the crisis period, where stocks do not react to Federal funds rate cuts, they positively respond in the non-crisis period.

The paper proceeds as follows. Section 3.2 provides an overview of the three-year operations in the context of the ECB's monetary policy. Section 3.3 presents the data and summary statistics. Section 3.4 presents the technicalities of the estimation approach. Section 3.5 presents the results. Section 3.6 concludes.

3.2 Overview of the Institutional Setting

In this section, we provide a brief overview of the ECB's monetary policy tools relevant to the study and the modalities of the three-year operations, including estimates of country-level liquidity uptake.

3.2.1 The ECB's Monetary Policy

Conventional liquidity-injecting monetary operations of the ECB are divided into open market operations and a standing facility (ECB, 2011). Table 3.1 offers an overview of the ECB operational framework. Main refinancing operations (MROs) and longer-term refinancing operations (LTROs) are the two main types of open market operations that allow the ECB to inject liquidity against collateral provided by the counterparty. MROs and LTROs are implemented on a recurring basis (MROs weekly, LTROs monthly) for a pre-specified duration (MROs one week, LTROs traditionally three months) in the form of reverse transactions.

Insert Table 3.1 around here.

Before October 7, 2008, when a bank applied for an MRO or LTRO loan it participated in an auction with the ECB by stating the interest rate that it is willing to pay for a certain amount of liquidity (variable-rate tender). The aggregate amount that the ECB offered to Eurozone banks was restricted ("liquidity neutral period," see Fecht, Nyborg, and Rocholl, 2011; Nyborg, Bindseil, and Strebulaev, 2002) to what banks, in the aggregate, need to fulfill reserve requirements.[6]

In the aftermath of the Lehman Brothers collapse on 15 September 2008 the money markets started to dry up, banks hoarded money because of fear of adverse selection on the interbank market, and short-term interest rate spreads rose. To avert an intensification of the crisis and to avoid increased credit rates for households and firms, many major central banks had to reduce policy interest rates.[7] Within seven months, the ECB iteratively reduced its key interest rate on MRO loans by a total of 325 basis points down to 1.00% (ECB, 2010). Eventually, on 15 October 2008, the ECB started a series of unconventional monetary policy measures which was later referred to as the *enhanced credit support* program. The new policy measures can be summarized into three main components: (i) fixed-rate full allotment procedure, (ii) eligible collateral list, (iii) additional LTROs of longer maturity.

The first component targets the *variable-rate fixed amount* LTROs that are usually auctioned off on a monthly basis. Using the *fixed-rate full allotment* tender procedure, the ECB started to offer any eligible counterparty to demand (a) unlimited central bank liquidity against adequate collateral for (b) a pre-determined fixed interest rate (at the time equal to the main refinancing rate of 1.00%). Secondly, the ECB enlarged both the list of *eligible collateral* being accepted for refinancing operations as well as the list of counterparties that may apply for fine-tuning operations (from 140 to approximately 2,000 counterparties). Thirdly, the ECB introduced new LTROs with longer maturities of up to six months (previously standard LTROs had a duration of one to three months). Table 3.2 lists the number of MRO and LTRO transactions per year, the average number of bidders per transaction, and the average allotted amounts per transaction for the period 2000 – 2013.

Insert Table 3.2 around here.

These non-standard measures were intended to back the short-term funding needs of counterparties, ease the banks' liquidity position, reduce the money market spreads, keep

[6] As explained by European Central Bank (2002), other autonomous factors can also play a role in determining the allotment size.

[7] In a concerted and joint statement the Bank of Canada, the Bank of England, the European Central Bank, the Federal Reserve, Sveriges Riksbank, and the Swiss National Bank announced policy rate reductions on 8 October 2008. The ECB key interest rate was reduced by 50 basis points on this day.

short-term interest rates at low levels, and preserve and improve the availability of credit to households and firms (ECB, 2010). As part of the credit enhancement program, the ECB again loosened the conditions for its LTRO liquidity-providing mechanism in June 2009. This time the ECB announced a fixed-rate full allotment extraordinary LTRO with a maturity of one year (instead of six months). The interest of counterparties was very high. As illustrated in Table 3.2, before the crisis, the average number of ECB counterparties participating in 3m-LTROs ranged from roughly 130 to 270. This number reached a new high with over 640 bidding banks on average (maximum of 1,121 counterparties on June 25, 2009) for the three 1y-LTRO allotments in 2009 providing average amounts of over EUR 200bn per transaction (with a maximum of EUR 442bn on June 25, 2009).

In the coming months markets started to stabilize, money market spreads declined, bond and stock markets recovered while loans to households started to grow and the survey of euro area banks on bank lending indicated less tightened credit standards on loans to firms (ECB, 2010). This led the ECB to announce a phasing-out of the non-standard measures in December 2009, i.e., the ECB declared that the LTRO allotment of December 2009 would be the last fixed-rate full allotment 1y-LTRO and that subsequent auctions would revert to the variable-rate tender procedure as used prior to the crisis.

Government bonds spreads of many large European peripheral countries such as Italy, Greece, Portugal, and Spain started to rise compared to the German Bund in early 2010 marking the start of the *European sovereign debt crisis*. The ECB reacted on 9 May 2010 by launching the Securities Market Programme (SMP) to restore depth and liquidity in debt securities markets (ECB, 2010). Additionally, the ECB reintroduced the fixed-rate full allotment procedure for three and six-month LTROs.

3.2.2 The Three-Year LTROs and Liquidity Uptake

Since markets did not improve, ECB announces the three-year LTROs on December 8, 2011, officially as a measure to "support bank lending and liquidity in the euro area money market."[8] However, on December 1, 2011, a few days before the official press release, the ECB's President, Mario Draghi, gives a speech to the European Parliament where one of his key points is the ECB's awareness of banks' maturity mismatches and stressed bank funding.[9] On that day an article in the Financial Times states that Draghi's speech is interpreted by the markets as an indication of the ECB to expand the Securities Markets

[8]See ECB press release, December 8, 2011: "ECB announces measures to support bank lending and money market activity," ecb.europa.eu.

[9]See FT Alphaville article by Izabella Kaminska, December 1, 2011: "Draghi: 'We are aware of the scarcity of eligible collateral'," ftalphaville.ft.com.

Programme or to announce three-year ECB loans.[10] In the event study, we take this pre-announcement into account by widening the event window up to $[-7, 7]$ days where, in trading days, the -5 represents December 1, 2011.

The modalities of the three-year LTROs are the same for all banks with access to Eurosystem liquidity operations. Interest is to be paid at maturity. The rate is fixed at the MROs' retrospective average rate over the respective period (three years). On the announcement day, the MRO rate was at 1%. The three-year LTROs include an option for early repayment after one year. Furthermore, after the first year and if the counterparties inform the respective national central bank one week ahead, they are allowed to repay (fully or partly) the allotted amounts on days coinciding with MRO settlements (every week). Counterparties are also allowed to transfer the outstanding amounts from the earlier conducted one-year LTRO (October 2011) into the first three-year LTRO.

The liquidity uptake is extraordinarily large in the three-year LTROs (see Crosignani et al., 2017). Table 3.3 lists the details of the extraordinary LTROs announced on December 8, 2011, and lists the uptakes and changes on outstanding OMO transactions.

INSERT TABLE 3.3 AROUND HERE.

Panel A in Table 3.3 lists the allotment, settlement, and redemption dates as well as the resulting maturity of the extraordinary LTROs. Liquidity uptake in the October 1y-LTRO was not unusually large. This was probably due to the low availability of eligible collateral. When markets turned worse, the ECB eventually announced the 3y-LTRO on December 8 with eased collateral requirements and a lower interest rate and replaced the originally planned second 1y-LTRO. The first settlement on December 22 amounted to 489.19bn Euro for 523 counterparties while the second settlement (March 1, 2012) equaled to 529.53bn Euro allotted to 800 counterparties. Panel B lists the outstanding amounts in MRO and LTRO financing in the week preceding the respective transaction. Eurozone banks did not only take up a lot of extraordinary LTRO money but also replaced a significant part of MRO, substantially prolonging the average maturity of their funding leg. This can be seen in Panel C: In the first 3y-LTRO settlement a total of 489.16bn was settled; in the same week the outstanding amount of MRO funding reduced by 122.61bn while the net amount of LTRO funding increased by 335.29bn. 153.91bn were thus used for substitution of existing ECB funding.

INSERT FIGURE 3.1 AROUND HERE.

Figure 3.1 displays the liquidity uptake over the period from 2006 to 2015. We observe that the settlement dates of LTROs led to a sharp increase in the LTRO position on

[10]See Financial Times article by Ralph Atkins, December 1, 2011: "Draghi hints at eurozone aid plan," ft.com (see also Krishnamurthy, Nagel, and Vissing-Jorgensen, 2015).

ECB's balance sheet. The total lending (MRO and LTRO combined) to euro area credit institutions increased by EUR 214.12bn to EUR 879.13bn (first settlement in 2011, marked as (2)), and by EUR 310.67bn to 1130.35bn (second settlement in 2012, marked as (3)). The large LTRO uptakes are partly compensated by reductions in the relatively shorter-term MROs. In 2011/2012 the combined net LTRO increase was +783bn while the MRO reduction amounted to -260bn. The lower panel of Figure 3.1 shows that the importance of main refinancing operations (MRO) decreased relatively to LTRO after the emergence of the crisis in 2007 and with settlements of the extraordinary LTRO allotments.[11]

Insert Figure 3.2 around here.

In Figure 3.2, we depict in the upper Panel A the weighted average remaining maturity of outstanding MRO and LTRO liquidity in days. We observe that mainly the three settlements of June 2009, December 2011 and March 2012 increased the remaining maturity of outstanding MRO and LTRO liquidity. The increases are very sharp and large due to the large size, longer maturity of the LTROs and the substitution of relatively shorter-term MRO liquidity.

Uptake in the three-year LTROs is unfortunately not publicly available on a country-level basis. However, some of the Eurosystem's national central banks provide statistics on MRO and LTRO liquidity outstanding on a monthly basis as collected by Bruegel (see Pisani-Ferry and Wolff, 2012). The position "LTRO" includes both standard outstanding three-month and extraordinary three-year liquidity. Unfortunately, the national central banks provide these figures in different formats (see Woschitz, 2017, for details). To provide estimates on LTRO liquidity uptake, we proceed as Woschitz (2017) and calculate a monthly average of outstanding MRO and LTRO liquidity for each country for which the national central bank provides these statistics separated into MRO and LTRO outstanding liquidity.[12] A monthly estimate of liquidity uptake from month m to month $m + 1$ can then be calculated by subtracting average outstanding liquidity in month m from that in month $m + 1$.

Table 3.4 estimates net liquidity uptake in MROs, LTROs, and in total over the two cash settlements of the three-year LTROs for those countries providing the respective figures separately. Panel A provides outstanding liquidity end of October 2011 and liquidity uptake from the beginning of November 2011 to the end of January 2012 as well as from the beginning of February to the end of April 2012, two periods which span over the first and second three-year LTRO cash settlements, respectively. Numbers are in million

[11] Fine-Tuning Operations, as well as the Marginal Lending Facility played only minor roles in terms of relative liquidity provided.

[12] For the Netherlands, Cyprus, and Malta, only total outstanding liquidity is publicly available. The total position is not separated into MRO and LTRO liquidity outstanding.

EUR. Countries are sorted according to LTRO uptake over the first cash settlement (in the period November 2011 to January 2012). Panel B calculates the percentage changes on outstanding liquidity end of October 2011 and January 2012.

Insert Table 3.4 around here.

Panel A shows that in most countries, banks substitute MRO by LTRO liquidity. Two exceptional cases, Ireland and Greece, actually reduce LTRO and even total borrowing over the cash settlements of both three-year LTROs. The largest uptakes over the first cash settlement period are taken by banks in Spain (EUR 112.0 bn), Italy (EUR 94.2 bn), France (EUR 68.6 bn), and Germany (EUR 24.2 bn). Notice that the aggregate uptake in Spain is more than four times larger than the one in Germany. The order of net uptake in MROs and LTROs for the four largest economies is the same over the second cash settlement with net uptake of EUR 160.2 bn in Spain, EUR 112.6 bn in Italy, EUR 36.6 bn in France, and EUR 30.3 bn in Germany.

Panel B shows that in relative terms, banks in Austria and Belgium increase their LTRO position by 125.8% and 169.2%, respectively. Relatively speaking this is more than what French banks take in the aggregate (107.3%). However, both Austrian and Belgium banks have with EUR 3.1 and 6.7 bn relatively little outstanding LTRO liquidity end of October 2011 (see Panel A). Portuguese banks increase LTRO liquidity only by 16.6% and 34.2% throughout the first and second cash settlements, respectively. Portuguese banks in the aggregate, however, have EUR 32.8 bn outstanding LTRO liquidity end of October 2011, which is roughly 1.7 times as much as the aggregate of German banks. Relatively speaking Finland shows the largest uptake of 2,096.2% over the first cash settlement, which results from the small EUR 0.1 bn outstanding LTRO liquidity end of October 2011.

Overall, these numbers provide evidence that – if one controls for the size of the economy of a country and outstanding liquidity end of October 2011 – in particular, the peripheral Eurozone countries make use of the three-year LTROs. This is in line with Nyborg (2017) who argues that the ECB provides an indirect bailout to these financially weaker countries and banks by offering the three-year liquidity.

3.3 Data and Summary Statistics

We use daily equity returns from Thomson Reuters Datastream. The unfiltered data covers 130 banks from 15 out of the 19 Eurozone countries: Austria (4 banks), Belgium (4), Finland (7), France (32), Germany (23), Luxembourg (1), Malta (3), Netherlands (6), Greece (4), Ireland (1), Italy (28), Portugal (4), Slovenia (1), Spain (11), and Cyprus

(1).[13] We only keep banks if the full return series from –192 business days before the announcement of the three-year LTROs (December 8, 2011) to 7 business days after the second cash settlement (March 1, 2012) is available. This covers the period from March 15, 2011, to March 12, 2012 (260 business days). We lose 2 Spanish banks because their time-series start only as of July 20 and 21, 2011. Furthermore, we drop banks with more than 35 zero return days ($\approx$ 13.5% of the 260 total business days) in an attempt to balance the loss of banks versus keeping too many whose equity does not trade.[14] Due to this filter we lose Ireland and Luxembourg (1 bank each) as well as a total of 36 banks located in Finland (3 banks), France (14), Germany (10), Greece (3), Italy (2), Malta (2), Netherlands (1), and Spain (1). Finally, we exclude Slovenia (1 bank) from the analysis because we have not found a Slovenian bank index in Datastream that trades well over the respective period. Therefore, our final bank sample consists of 89 banks in 12 countries observed on 260 business days (23,140 bank-day observations), whereby each security trades on at least 225 days (86.5% of the 260 total business).

For each country in the bank sample, we download a total market as well as a total bank return index from Datastream.[15] We work with the following total *market* return indices (by country):

> "ATX" (Austria), "BEL 20" (Belgium), "OMX Helsinki" (Finland), "CAC 40" (France), "DAX 30" (Germany), "STOXX Malta", "AEX all-share" (Netherlands), "ATHEX" (Greece), "FTSE MIB" (Italy), "PSI all-share" (Portugal), "IBEX 35" (Spain), and "STOXX Cyprus". In robustness checks, we use the overall European Union index "STOXX Europe 600".

For further robustness checks, we use the following total *bank* return indices:

> "FTSE Austria Banks", "FTSE Belgium Banks", "NOMXH Banks (Finland)", "FTSE France Banks", "FTSE Germany Banks", "Malta-DS Banks", "Netherland-DS Banks", "FTSE Greece Banks", "FTSE Italia all-shr Banks", "FTSE Portugal Banks", "FTSE Spain Banks", and "Cyprus-DS Banks".

Table 3.5 provides summary statistics by country. Panel A shows descriptive statistics for the bank equity return sample. For Malta, Greece, and Cyprus, the sample contains only one bank. Italy exhibits with 26 banks the maximum number of banks per country followed by France (18 banks) and Germany (13). Over the total 260 business days the

[13] The raw sample does not contain banks from the Eurozone countries Latvia, Slovakia, Estonia, and Lithuania.

[14] Notice that zero return days can also be country-specific holidays, for instance, where trading does not take place because an exchange is closed.

[15] In line with the literature, we use the total return index as our main return variable since it accounts for potential dividend payments which would be re-invested at the closing price on the ex-dividend date.

maximum percent of zero returns is observed in Greece with 10.77% followed by France (7.54%) and Austria (7.40%). The same statistic for the three [–7,7] event windows shows that Austria exhibits with 13.75% the maximum percent of zero returns in the sample, followed by Greece with 12.50%.[16] On average, bank equity returns are negative in all countries except for Malta (4 bps). The lowest average is observed in Greece with –37 bps. Spanish banks exhibit both the minimum (–28.38%) and maximum (40.38%) return over the sample period. The second-highest minimum return is held by the Greek bank (–28.02%) and the second-highest maximum by an Italian bank (33.17%). In the pooled sample as well as in most countries the median is zero or close to mean value which provides evidence that the bank equity returns are nicely behaved in terms of the normality assumption.

Insert Table 3.5 around here.

Panel B shows summary statistics for equally-weighted bank equity return portfolios built across the banks in Panel A per country. For each country, we now observe 260 business days out of which 40 business days belong to at least one event window used later on (see footnote 16). In total, the sample comprises 3,120 country-day observations. For Malta, Greece, and Cyprus – with only one bank in the sample – values in Panel B are the same as in Panel A. Abstracting from those countries, the number of zero returns over the full sample period of 260 business days reduces drastically from between 2.60% (Belgium) and 7.54% (France) in Panel A to between 1.15% (Belgium, France, Germany, Netherlands, and Portugal) and 2.31% (Austria) in Panel B. The same observation is made for zero returns on business days that are included in at least one event window: zero returns reduce from between 2.50% (Belgium) and 13.75% (Austria) in Panel A to between 2.5% (Belgium, Finland, France, Germany, Netherlands, Italy, Portugal, and Spain) and 5% (Austria) in Panel B. For countries with more than one bank in the sample, Portugal provides the minimum and maximum observed return with –10.63% and 11.63%. Including countries with only one bank in the sample, Greece leads this statistic (minimum: –28.02%, maximum: 29.52%) followed by Cyprus (minimum: –16.38%, maximum: 25.76%).

Panel C provides summary statistics for the market return indices for each country. Again, for each country, we observe 260 business days out of which 40 business days belong to at least one event window. The last row in Panel C shows the summary statistics for

[16] The event window figure includes days of all three event windows that we study later on. This figure, therefore, includes the [–7,7] = 15 business days around December 8, 2011, December 22, 2011, and March 1, 2012. This is a total of 45 business days. However, the sub-windows [3,7] from event one (December 8) and [–7,–3] from event two (December 22) overlap, which reduces the number of overall event days by five days. Thus, the figure discussed includes in total 40 event days.

the "STOXX Europe 600" index. The highest numbers of zero returns across the full 260 business days are observed in Malta with 11.54%, followed by Austria with 4.62%. The non-peripheral countries exhibit zero returns of between 1.15% and 3.46%. Restricting the sample to days used in at least one event window shows that the same two countries exhibit the highest percentage of zero return days: Malta with 17.50% and Austria with 7.50%. The non-peripheral countries exhibit percentages between 2.50% and 5.00%. Even the "STOXX Europe 600" index does not trade on 1.15% of the full 260 business days and 2.50% of days classified as event days. The mean returns are negative in all countries except for Germany.

Panel D shows the summary statistics for the bank index sample that we use in robustness checks. Over the full 260 business days, we observe between 0.00% (Netherlands) and 4.62% (Austria) zero returns. The same statistic for the 40 days classified as event days shows that zero returns make up for between 0.00% (Malta and Netherlands) and 7.50% (Austria) of the observed event days. Across the full 260 sample days, the mean return is negative in all countries.

3.4 Event Study: Methodology

We study the impact of the announcement and the two cash settlements of the three-year LTROs separately on end-of-day stock prices of Eurozone banks. Therefore, an important issue that this study has to deal with is the fact that we examine (cumulative) abnormal returns in a cross-section of bank stocks using only one event which is the same for the whole industry (banks). In this section, we explain how we calculate (cumulative) abnormal returns and how we attempt to overcome this issue.

We estimate abnormal bank equity returns using the standard market model approach as lined out by MacKinlay (1997).[17] We set $t = 0$ as the event date (for each of the three events – the announcement and the two cash settlements – separately), the period T_0 to T_1 as estimation window, and T_2 to T_3 as event window. The abnormal return for bank i on date t is calculated as

$$AR_{i,t} = r_{i,t} - E[r_{i,t}|r_{m,t}], \tag{3.1}$$

where $r_{i,t}$ is the realized and $E[r_{i,t}|r_{m,t}]$ the expected return on bank stock i on date t. The latter term is estimated from a market model using the realized return on the market, $r_{m,t}$, with a regression model of the form

$$r_{i,t} = \beta_{i0} + \beta_{i1} r_{m,t} + \beta_{i2} r_{m,t-1} + \beta_{i3} r_{m,t+1} + \epsilon_{i,t}. \tag{3.2}$$

[17] For an extensive survey of event studies applied in the context of banking see Degryse, Kim, and Ongena (2009).

Adding lead and lag ($r_{m,t-1}$ and $r_{m,t+1}$) of the market index $r_{m,t}$ helps control for non-synchronous trading. The market model is estimated individually per bank using the estimation window $[T_0, T_1] = [-192, -8]$.[18] The cumulative abnormal return for bank i is then calculated by summing up the abnormal returns over the event window $[T_2, T_3]$,

$$CAR_{i,[T_2,T_3]} = \sum_{t=T_2}^{T_3} AR_{i,t}. \tag{3.3}$$

As we are interested in the impact of the three-year LTROs on bank equity on a country-level we average both abnormal and cumulative abnormal returns across banks within a country,

$$AR_{c,t} = \frac{1}{N_c} \sum_{i=1}^{N_c} AR_{i,t} \quad \text{and} \quad CAR_{c,[T_2,T_3]} = \frac{1}{N_c} \sum_{i=1}^{N_c} CAR_{i,[T_2,T_3]}, \tag{3.4}$$

where N_c is the number of banks in country c. We show estimated $CAR_{c,[T_1,T_2]}$ not only for the full event window $[T_2, T_3] = [-7, 7]$ but also for shorter windows $[0, 1]$, $[0, 3]$, $[-1, 1]$, $[-1, 3]$, $[-3, 3]$, and $[-5, 5]$ to evaluate the effect of each event in more detail.[19] We evaluate economic magnitudes using these definitions of (cumulative) abnormal returns.

To assess the statistical significance of the (cumulative) average abnormal returns, we use two established test statistics. First, we use the crude dependence adjustment (CDA) test by Brown and Warner (1980). This test statistic accounts for cross-correlations of abnormal returns by calculating the standard deviation on country-level abnormal returns across days in the estimation window. The test statistic for the country-level abnormal return on date t is calculated as

$$t_{BW,AR_{c,t}} = \frac{AR_{c,t}}{S_{AR_c}}, \tag{3.5}$$

where

$$S_{AR_c} = \sqrt{\frac{1}{185 - 4} \sum_{t=T_0}^{T_1} (AR_{c,t} - \overline{AR_c})^2} \tag{3.6}$$

[18] This procedure to calculate $AR_{i,t}$ yields in our case the same result as using both the estimation and the event window and running the regression $r_{i,t} = \beta_{i0} + \beta_{i1} r_{m,t} + \beta_{i2} r_{m,t-1} + \beta_{i3} r_{m,t+1} + \sum_{k=T_2}^{T_3} \gamma_{i,k} \delta_{i,k,t} + \epsilon_{i,t}$, where $\delta_{i,k,t}$ is an indicator variable for date k. Each of these 15 indicator variables takes on the value 1 on one of the 15 days in the event window and is zero on the other days. The coefficient $\gamma_{i,k}$ measures the abnormal return on day k.

[19] A short event window has the advantage of minimizing the effects of confounding events (Degryse et al., 2009). However, it runs the risk of missing the effect of complex information that requires time to be incorporated in stock prices (Gagnon et al., 2011).

and $\overline{AR_c}$ is the average abnormal return across daily observations in the estimation window.[20] The term $185-4$ subtracts the number of parameters estimated in Eq. 3.2 from the number of daily observations in the estimation window.[21] The test statistic for cumulative abnormal returns is calculated as

$$t_{BW,CAR_{c,[T_1,T_2]}} = \frac{CAR_{c,[T_1,T_2]}}{\sqrt{(T_3 - T_2)}\ S_{AR_c}}. \tag{3.7}$$

This procedure is one way to control for cross-correlation. Brown and Warner (1980) show that their test statistic is robust to event-induced changes in variance. Harrington and Shrider (2007) demonstrate that cross-sectional variation in the abnormal returns always produces event-induced variance. Not controlling for it renders the independence assumption for the abnormal returns incorrect and may lead to over-rejections of the null hypothesis for zero abnormal returns (Kothari and Warner, 2007). However, we examine (cumulative) abnormal returns in a cross-section of bank stocks using only one event, which is the same for the whole industry (banks). The Brown and Warner (1980) test statistic does not explicitly control for this type of cross-correlation.

The second test statistic used is developed by Kolari and Pynnönen (2010). The authors propose a correction term (which controls explicitly for cross-correlation) to the test statistic developed by Boehmer et al. (1991). The latter test statistic is based on standardized abnormal returns, as proposed by Patell (1976). The Patell (1976) test statistic standardizes abnormal returns by the regression residual standard deviation and a correction term to reduce the weight of more volatile observations (forecast error), as

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{AR_{i,t}}}, \tag{3.8}$$

where

$$S^2_{AR_{i,t}} = S^2_{AR_i}\left(1 + \frac{1}{185} + \frac{(r_{m,t} - \overline{r}_m)^2}{\sum_{t=T_0}^{T_1}(r_{m,t} - \overline{r}_m)^2}\right), \tag{3.9}$$

and

$$S^2_{AR_i} = \frac{1}{185-4}\sum_{t=T_0}^{T_1} AR^2_{i,t}. \tag{3.10}$$

[20] Notice that using the Brown and Warner (1980) test statistic to assess statistical significance in the bank stock sample is in our case very similar to first averaging bank equity returns into an equally-weighted portfolio per country, running the market model on the country-level (essentially this is one regression per country), and assessing the statistical significance of $AR_{c,t}$ with a simple t-test in this sample.

[21] The statistic is Student-t distributed with $T-4$ degrees of freedom under the null hypothesis of zero abnormal returns (see Serra, 2002).

The term $\overline{r}_m$ represents the average market returns during the estimation window, and the term in brackets is the forecast error. Using this approach of standardized abnormal returns, Boehmer et al. (1991) estimate a cross-sectional standard deviation on the event day which then controls for event-induced changes in variance. The authors propose the test statistic

$$z_{BMP,ASAR_{c,t}} = \frac{\sqrt{N_c}\ ASAR_{c,t}}{S_{ASAR_{c,t}}} \tag{3.11}$$

where $ASAR_{c,t}$ is defined as the average of the standardized abnormal returns, $SAR_{i,t}$, across the N_c banks in country c for date t,

$$ASAR_{c,t} = \frac{1}{N_c} \sum_{i=1}^{N_c} SAR_{i,t}, \tag{3.12}$$

and its standard deviation as

$$S_{ASAR_{c,t}} = \sqrt{\frac{1}{N_c - 1} \sum_{i=1}^{N_c} \left(SAR_{i,t} - \frac{1}{N_c} \sum_{l=1}^{N_c} SAR_{l,t} \right)^2}. \tag{3.13}$$

Notice that standardized (cumulative) abnormal returns are only used to assess statistical (not economic) significance.[22] Boehmer et al. (1991)'s test statistic for standardized cumulative abnormal returns is given by

$$t_{BMP,CAR_{c,[T_1,T_2]}} = \frac{CSAR_{c,[T_2,T_3]}}{S_{CSAR_{c,[T_2,T_3]}}} \tag{3.14}$$

where bank-level standardized abnormal returns are cumulated over the event window,

$$CSAR_{i,[T_2,T_3]} = \sum_{\tau=T_2}^{T_3} SAR_{i,t}, \tag{3.15}$$

and the cross-sectional average is calculated by taking the mean of the bank-level standardized cumulative abnormal returns of all the N_c banks in country c,

$$CSAR_{c,[T_2,T_3]} = \frac{1}{N} \sum_{i=1}^{N_c} CSAR_{i,[T_2,T_3]}. \tag{3.16}$$

[22]Standardized (cumulative) abnormal returns have less meaningful interpretation than their non-standardized counterparts (see Kolari and Pynnönen, 2010).

The standard deviation of $CSAR_{c,[T_2,T_3]}$ is estimated from the cross-section of event-window standardized cumulative abnormal returns as

$$S_{CSAR_{c,[T_2,T_3]}} = \sqrt{\frac{1}{N_c(N_c-1)} \sum_{i=1}^{N_c} \left(CSAR_{i,[T_2,T_3]} - CSAR_{c,[T_2,T_3]} \right)^2}. \tag{3.17}$$

Boehmer et al. (1991) provide evidence that their test statistic is comparable in size to the one of Brown and Warner (1980) but has more power. If the event affects the variances, Boehmer et al. (1991)'s test statistic controls for the variance change by cross-sectionally estimating the average of variance on the event day (Kolari and Pynnönen, 2010). Otherwise, it collapses into the Patell (1976) test statistic.

However, the Boehmer et al. (1991) test statistic does not control for cross-correlation. Thus, we make use of the Kolari and Pynnönen (2010) correction that adjusts Boehmer et al. (1991)'s test statistic and controls for both event-induced changes in variance and cross-correlation. Based on Boehmer et al. (1991), Kolari and Pynnönen (2010) propose the test statistic

$$t_{KP,ASAR_{c,t}} = z_{BMP,ASAR_{c,t}} \times \sqrt{\frac{1-\overline{r}}{1+(N_c-1)\overline{r}}}, \tag{3.18}$$

which corrects Boehmer et al. (1991)'s test statistic with the term under the square root. $\overline{r}$ is the estimation period mean sample cross-correlation of the residuals. Assuming that the square-root rule holds for the standard deviation of different periods for the returns, the statistical significance of cumulative abnormal returns can be assessed using the same adjustment to Boehmer et al. (1991)'s cumulative abnormal return test statistic (see Kolari and Pynnönen, 2010).

3.5 Event Study: Results

In this subsection, we present the event study results. First, we compare average abnormal returns on event days to those on non-event days. Second, we discuss cumulative abnormal returns that are calculated over different event windows. Third, we assess the statistical significance of the cumulative abnormal returns in more detail. Moreover, fourth, we describe conducted robustness checks.

3.5.1 Average Abnormal Returns: Event versus Non-Event Days

Table 3.6 shows the results of two-sample t-tests for equal means, Kruskal-Wallis χ^2-tests for equal medians, and variance-ratio F-tests for equal variances comparing event and non-event days, as shown in Delaloye, Habib, and Ziegler (2012). Countries are classified into peripheral and non-peripheral countries. Each of the three panels provides sample means, medians, and standard deviations (given as percentages) as well as the number of observations on event days and non-event days. For each event and each country the tests are based on $[-192, -8] = 185$ non-event days (estimation window) and $[-7, 7] = 15$ event days (event window).[23] Panel A shows these tests for the announcement of the three-year LTROs on December 8, 2011, and Panel B (Panel C) for the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). Test statistics and corresponding means, medians, and/or standard deviations that are statistically significant at a level of at least 10% are marked in bold. a, b, and c next to the test statistics denote significance at the levels of 1%, 5%, and 10%, respectively.

Insert Table 3.6 around here.

Panel A provides the results using the three-year LTRO announcement as the event day ($t = 0$). The results of the two-sample t-tests show that in particular the peripheral countries profit in terms of average abnormal returns over the event window of $[-7, 7]$ days around December 8, 2011. The only exception is Greece (one bank). The Greek bank exhibits a daily average abnormal return over the 15 days event window of -2.72%. Abstracting from Greece, the daily average abnormal return for peripheral countries lies between 42.5 bps (Portugal) and 102.1 bps (Spain). In non-peripheral countries, abnormal returns range from 6.0 bps (France) to 43.5 bps (Malta). The average abnormal returns of 102.1 and 63.8 bps on event days in Spain and Italy, respectively, are statistically different from those of 0.0 bps on non-event days at the significance levels of 5% and 1%. As seen in Table 3.4, Spanish and Italian banks also have the largest liquidity uptakes in both operations, which is in line with Nyborg (2017)'s indirect bailout argument. Notice that in all countries (except Greece) the daily average abnormal returns are positive on event days showing that banks in all countries profit from positive abnormal returns on their equity. Peripheral banks (except for the Greek bank), however, profit on average more. The Kruskal-Wallis χ^2-tests for equal medians provide similar results both in terms of economic magnitudes and statistical significance except for Austria and Finland where abnormal returns on event days are statistically significantly higher compared to those on non-event days.

Panel B shows the results using the first cash settlement as the event day. Neither the two-sample t-statistics nor the Kruskal-Wallis χ^2-statistics provide evidence for statistical

[23]Notice that the means of abnormal returns on non-event days across events and countries are zero. This feature comes from the fact that non-event days in our sample correspond to the days in the estimation window and by construction, the abnormal returns must be zero due to the OLS procedure that we use to estimate the market model.

significance. The only two countries with banks abnormally losing on their equity prices are the Netherlands and – as in Panel A – Greece. In all non-peripheral countries, daily average abnormal returns on event days are larger than on non-event days. Abstracting from the Netherlands and Greece, the average daily abnormal returns range from 7.4 bps (Spain) to 64.7 bps (Cyprus, only one bank) in peripheral countries and from 3.6 bps (France) to 42.1 bps (Malta, only one bank) in non-peripheral countries. Even if in most countries banks profit abnormally from increased equity prices over the first cash settlement, banks in peripheral countries profit more (abstracting from Greece). Again, the Kruskal-Wallis χ^2-tests provide similar results both in terms of economic magnitudes and statistical significance.

Panel C shows the results using the second three-year cash settlement as the event day. As expected the results are mixed for the second cash settlement which is in line with the argument that the large uptake in the second three-year LTRO was less of a surprise for the market because of the large uptakes in the first three-year LTRO.

The results so far provide first evidence that in particular peripheral countries profit in terms of abnormal returns on their equity over the announcement and first cash settlement.

3.5.2 Cumulative Abnormal Returns

This subsection shows country-level cumulative abnormal returns calculated as averages across cumulative abnormal returns of banks within a country (see Section 3.4). Notice that in this and the two subsequent subsections, we use the acronym $CAAR$, instead of CAR_c, for "cumulative average abnormal returns" (country-level cumulative abnormal returns) to keep the reading flow. Figure 3.3 plots the results over the event window $[-7, 7]$ for the three different events separately. The three columns of subplots represent the three events (the announcement, the first cash settlement, and the second cash settlement), respectively, as indicated by vertical lines in each subplot. The vertical line on December 1, 2011, in the first column of subplots, represents the ECB's first indication of large-scale help for Eurozone banks. Each line represents one country as indicated in the figure.

Insert Figure 3.3 around here.

Panel A compares $CAARs$ of Germany, France, and the peripheral countries (except for Greece) over the event window $[-7, 7]$ around the announcement date. All countries profit abnormally in terms of bank equity prices. However, banks in peripheral countries profit more than German and French banks. Panel B shows that bank equity performs similarly in other non-peripheral countries. German, French, and Finish bank stocks exhibit only small positive abnormal returns. The $CAARs$ in the Netherlands, Austria, Belgium, and Malta lie between the $CAARs$ in France (the minimum) and Spain (the maximum). Panel C shows that Greece (one bank) is a particular case. The Greek bank loses abnormally over the announcement period of the three-year LTROs. Across all three panels, $CAARs$ start to increase (except for Greece) as of December 1, 2011, which represents the first ECB statement about its awareness of banks' funding difficulties.

The subplots in the middle column show $CAARs$ over the event window $[-7, 7]$ around the first cash settlement. $CAARs$ develop similarly in Germany, France, Italy, and Spain. The middle column of subplots across panels shows no jump in $CAARs$ on the cash settlement day of the first three-year LTRO. However, the first cash settlement takes place on a Thursday. Stock prices of banks in Greece, Cyprus, and Portugal react abnormally from Monday to Tuesday the following week (2 and 3 business days after the cash settlement).

The third column of subplots provides the results for the second three-year cash settlement. Not surprisingly the results are rather unspectacular except for Cyprus, with the one sample bank exhibiting a large positive abnormal return on the cash settlement day. Furthermore, some of the non-peripheral countries show slightly increasing $CAARs$ but compared to the announcement and first cash settlement the positive $CAARs$ are negligibly small.

Table 3.7 provides the numbers for the full event window of $[-7, 7]$ days and six further sub-windows as indicated in the table. Panel A shows the results for the announcement of the three-year LTROs on December 8, 2011, and Panel B (Panel C) for the first (second) cash settlement on December 22, 2011 (March 1, 2012). Significance is evaluated using the test statistic proposed by Brown and Warner (1980), which is presented in brackets underneath the $CAARs$. $CAARs$ are marked in bold if significant at the level of at least 10%. a, b, and c next to the $CAARs$ denote significance at levels of 1%, 5%, and 10%, respectively. Numbers are given in decimals.

INSERT TABLE 3.7 AROUND HERE.

Panel A reveals that positive abnormal returns are particularly high for banks in peripheral countries over the announcement period. As already seen in Figure 3.3, the only exception is Greece. The Greek bank exhibits $CAARs$ of -18.1% and -40.8% over the windows $[-1, 3]$ and $[-7, 7]$, respectively, which are statistically different from zero at significance levels of 5% and 10%. Abstracting from Greece, 8 out of the 28 $CAARs$ in peripheral countries are significant at the level of at least 5% (which represents 28.6%). In terms of economic magnitudes, significant $CAARs$ range from 4.0% in Italy to 15.3% in Spain over the windows $[-3, 3]$ and $[-7, 7]$, respectively. Looking at shorter windows, only the $CAARs$ of 5.3% and 7.1% in Portugal over the windows $[0, 1]$ and $[-1, 1]$, respectively, are significantly different from zero. In the non-peripheral countries, $CAARs$ are significantly different from zero in 4 out of the 49 country-window combinations (8.2%)

at significance levels of at least 10%. Statistically significant *CAARs* range from −4.9% in Austria to −3.1% in the Netherlands over the windows $[0, 3]$ and $[-1, 3]$, respectively.

Panel B shows a similar picture for *CAARs* around the first three-year cash settlement. In peripheral countries, *CAARs* lie between 4.4% in Italy and 16.0% in Portugal over the window $[-5, 5]$ if they are statistically significant at levels of at least 10%. Across peripheral country-window combinations, 5 out of the 35 *CAARs* are statistically different from zero (14.3%). Across non-peripheral countries, Belgium is the only country with at least one *CAAR* (6.5% over the window $[-5, 5]$) statistically different from zero. Across all non-peripheral country-window combinations, this represents 2.0%.

Panel C shows the results for the second three-year cash settlement on March 1, 2012. Not surprisingly significance in Panel C is absent. The only exception is Cyprus (one bank). As seen in Figure 3.3, the Cypriot bank profits abnormally on the day of the cash settlement itself. The *CAAR* is 23.0% over the window $[0, 1]$ and statistically different from zero at the significance level of 1%.

The results provide evidence that over the announcement and the first cash settlement periods first and foremost peripheral countries (except for Greece) profit. According to statistically significant *CAARs*, non-peripheral countries even lose abnormally in terms of their equity prices over the announcement period. Furthermore, high *CAARs* seem to line up with large liquidity uptakes as seen in Table 3.4. The largest and second-largest LTRO uptakes (including standard LTRO liquidity) of approximately EUR 160 and 113 bn were made by Spanish and Italian banks in the second three-year LTRO (corresponding numbers for the first operation are EUR 112 and 94 bn, respectively). Spanish and Italian banks take approximately 4.6 and 3.9 times as much LTRO liquidity as German banks throughout the first cash settlement (corresponding multiples for the second cash settlement are 5.3 and 3.7, respectively). Thus, the results are in line with Nyborg (2017)'s argument of the indirect bailout.

3.5.3 Assessment of Statistical Significance

In this subsection, we reproduce Table 3.7 from the previous subsection but provide statistical significance with the test statistics of Kolari and Pynnönen (2010) and, for the sake of comparison, Boehmer et al. (1991). Throughout this subsection, we are going to use the acronyms "BMP" for Boehmer et al. (1991) and "KP" for Kolari and Pynnönen (2010). The comparison allows us to better understand the cross-correlation structure across banks within a country. KP's adjustment scales down BMP's test statistic if abnormal returns of banks within a country are, on average, positively correlated (in the estimation window). For instance, if the average of cross-correlations of abnormal returns of four bank stocks is $\bar{r} = 0.25$ and BMP's test statistic takes on a value of 2.0

(significant at the level of 1%) then KP suggest to multiply the value of BMP's test statistic by $\sqrt{(1-\bar{r})/(1+(N_c-1)\bar{r})} = 0.4472$, which results in an adjusted value for the test statistic of $2.0 \times 0.447 = 0.894$ (not significant even at the level of 10%). We restrict the analysis to countries with more than one bank in the sample because the calculation of both test statistics is based on the cross-section of banks within a country.

Table 3.8 provides the results. BMP's test statistic is presented in round brackets underneath the *CAARs*. KP's test statistic is presented in square brackets underneath BMP's test statistic. *a*, *b*, and *c* next to the *CAARs* denote significance at the levels of 1%, 5%, and 10%, respectively, with the BMP test statistic and, in square brackets, the KP test statistic.[24] *CAARs* that are significant at the level of at least 10% with the BMP test statistic are marked in bold. Numbers are given in decimals.

Insert Table 3.8 around here.

Comparing statistical significance with BMP in Table 3.8 and Brown and Warner (1980)'s test statistic in Table 3.7 shows that, even if both tests are robust to event-induced variance, the *CAARs* are more often significant with the BMP as compared to the Brown and Warner (1980) test statistic. This is due to its higher power.

Panel A shows *CAARs* over the announcement period of the three-year LTROs. In the peripheral (non-peripheral) countries using the BMP test statistic 9 (11) out of the 21 (42) country-window combinations for *CAARs*, which represents 42.9% (26.2%), are statistically significantly different from zero at the significance level of at least 10%. In peripheral countries, statistically significant *CAARs* lie between 1.7% in Italy and 15.3% in Spain over the windows $[-1, 1]$ and $[-7, 7]$, respectively. The corresponding numbers for non-peripheral countries are -4.9% in Austria and 5.4% in Germany over the windows $[0, 1]$ and $[-7, 7]$, respectively. Using the KP test statistic instead leaves only the *CAAR* of 11.7% in Spain over the window $[-5, 5]$ statistically significant at the level of 10% in peripheral countries. Notice, however, that the *CAARs* of 4.0%, 6.3%, and 9.6% in Italy over the windows $[-3, 3]$, $[-5, 5]$ and $[-7, 7]$, respectively, have KP t-statistics of 1.593, 1.589, and 1.527 which result in p-values of 11.3%, 11.4%, and 12.9%. Using the KP test statistic in the non-peripheral countries leaves 7 out of the 42 country-window combinations statistically significant covering the same range of *CAARs* as with the BMP test (-4.9% in Austria and 5.4% in Germany).

Panel B shows *CAARs* over the first cash settlement period. In peripheral countries, 7 out of the 21 statistically significant *CAARs* (using BMP test) lie between -2.1% in Spain and 16.0% in Portugal over the windows $[0, 3]$ and $[-5, 5]$, respectively. Correspondingly,

[24]Notice that we provide the BMP test statistic first not because it is the more relevant test statistic but because it makes results more visible in Table 3.8.

in non-peripheral countries, 7 out of 42 statistically significant abnormal returns range from -0.9% in the Netherlands to 4.0% in Germany over the windows $[0, 3]$ and $[-7, 7]$, respectively. Using the KP test statistic in the peripheral countries leaves only the $CAAR$ of 2.3% in Spain over the window $[-5, 5]$ statistically different from zero at the level of 10%. Correspondingly for the non-peripheral countries, the KP test statistic leaves only the 1.9% $CAAR$ in Finland over the window $[-5, 5]$ statistically significant (at the 5% level).

The results in Panels A and B support the previous findings that $CAARs$ are higher for banks in peripheral than in non-peripheral countries if they are statistically significant with the KP test-statistic. The comparison of test statistics reveals a higher correlation across bank stocks in peripheral countries, in particular over the announcement period, than in non-peripheral countries. Furthermore, notice that the $CAAR$ of 16.0% for Portugal in the window $[-5, 5]$ has a KP t-statistic of 1.563 that results in a p-value of 12.0%. Crosignani et al. (2017) show that Portuguese banks ran "collateral trades" on high-yielding Portuguese sovereign bonds using the three-year liquidity uptake. Essentially this means that Portuguese banks have invested the three-year uptake into Portuguese sovereign debt, which provides evidence in line with Nyborg (2017) that these operations have served as indirect bailout not only for financially weaker banks (which is supported by the $CAARs$) but also to weaker sovereigns.

Panel C shows $CAARs$ over the second cash settlement period. Using the KP test statistic for the peripheral countries leaves only the $CAAR$ of -11.0% in Portugal over the window $[-7, 7]$ to be statistically different from zero at the level of 5%. Using the KP test statistic for the non-peripheral countries leaves 8 out of the 42 country-window combinations statistically significant covering the range of $CAARs$ from 0.9% in Belgium to 4.2% in Austria over the windows $[0, 1]$ and $[-5, 5]$ respectively. The results in Panel C are generally (also with the BMP test statistic) more mixed across peripheral and non-peripheral countries.

Overall, these results echo the previous findings even if we control for cross-correlation of abnormal returns on bank stocks across banks within a country (using the Kolari and Pynnönen, 2010, or KP, test statistic).

3.5.4 Robustness Checks

We ran a number of robustness checks similar to Nyborg (2017). First, we examine whether we receive the same results if we build equally-weighted portfolios of bank stock returns and use that sample for the event study. Table C-1 in the appendix compares average abnormal returns on event to non-event days (the equivalent to Table 3.6) for the equally-weighted portfolio sample. Not surprisingly the results are practically identical because the only difference is the order of running the market model regressions and the averaging process. Due to the lower number of observations for countries with more than one bank in the sample, test statistics are generally less significant. Nevertheless, the findings in terms of evaluating statistically significant means and medians remain the same compared to Table 3.6. Results remain basically the same in Panels B and C for the first and second cash settlements, respectively. As described in Footnote 20 also, the assessment of statistical significance for the $CAARs$ remains unchanged.

Second, instead of using country-level total market return indices as described in Section 3.3, we use the "STOXX Europe 600" index as the market index for each country. Table C-2 in the appendix shows that the results for the comparison of means and medians of abnormal returns on event versus non-event days are both qualitatively and quantitatively very similar to the results in Table 3.6. Results for the analysis of the $CAARs$ are provided in the Tables C-3 and C-4 as well as in Figure C-1 in the appendix (these are the equivalents to the Tables 3.7 and 3.8 as well as Figure 3.3, respectively). Again, both qualitatively and quantitatively the results are very similar to the previous findings independent of the applied test statistic (Boehmer et al., 1991; Brown and Warner, 1980; Kolari and Pynnönen, 2010).

Third, instead of using bank stock-level data, we use total return bank indices for each country (see Section 3.3 for an overview). Comparing Figure C-2 in the appendix to Figure 3.3 shows a few noteworthy differences. Results with the bank index sample show that $CAARs$ are smaller over the announcement period of the three-year LTROs as compared to results with the bank stock-level sample. Furthermore, also non-peripheral countries profit from abnormal returns over the announcement period (in particular, France from December 1 to 8, 2011). However, the positive abnormal returns over the first cash settlement two weeks later, on December 22, 2011, are higher for Cyprus and Portugal than they are in Figure 3.3. Using country-level bank indices seems to shift the higher abnormal returns in peripheral countries, as compared to non-peripheral countries, from the announcement to the first cash settlement of the three-year LTROs. Both Tables C-5 and C-6 in the appendix confirm these findings also in terms of economic magnitudes and statistical significance (these are the equivalents to Tables 3.6 and 3.7, respectively). Both the economic magnitudes and the statistical significance are lower for peripheral countries over the announcement period but higher over the first cash settlement period of the three-year LTROs, in particular in Portugal and Cyprus.

Overall, the robustness checks confirm the results of the principal analysis. However, using country-level bank indices instead of bank stock-level data shifts the effects from the announcement of the three-year LTROs to the first cash settlement. Banks in peripheral countries profit more as compared to non-peripheral countries in particular over the first cash settlement period in terms of abnormal equity price increases.

3.6 Conclusion

This study uses an event study to examine the impact of the ECB's three-year LTROs on banks' stock prices. Compared to other studies, we exclusively focus on the three-year LTROs and bank equity. The study aims at comparing (cumulative) abnormal returns across Eurozone countries using a variety of tests to assess the statistical significance. In the main setup, the paper estimates a market model to predict abnormal returns on 89 bank stocks from 12 different Eurozone countries with country-level total market return indices (the data is from Thomson Reuters Datastream).

The results provide evidence that over the announcement and the first cash settlement periods banks in peripheral countries profit more compared to banks in non-peripheral countries. The only exception is Greece (one bank in the sample). The Greek bank loses abnormally in terms of its equity price, especially over the announcement period. As expected, we find no differential results across peripheral and non-peripheral countries over the second cash settlement.

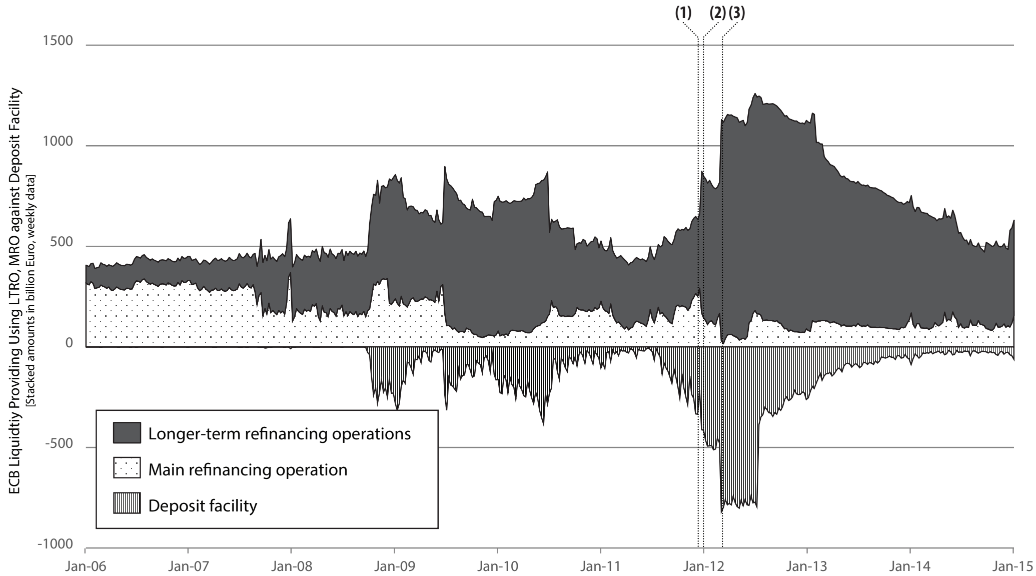
Even if we use the test statistic developed by Kolari and Pynnönen (2010), which controls explicitly for cross-correlation and renders many country-level cumulative abnormal returns ($CAARs$) insignificant, we find that Spanish banks, on average, exhibit a $CAAR$ of 11.7% over the window of $[-5, 5]$, which is significant at the level of 10%. Spanish banks have, at the same time, the largest liquidity uptake over both cash settlement periods. $CAARs$ for Italian banks of 4.0%, 6.3%, and 9.6% over the event windows of $[-3, 3]$, $[-5, 5]$, and $[-7, 7]$ have p-values of 11.3%, 11.4%, and 12.9%, respectively. Italian banks have the second-largest liquidity uptake. At the same time, statistically significant $CAARs$ in non-peripheral countries lie between -4.9% in Austria and 5.4% in Germany for the windows $[0, 1]$ and $[-7, 7]$, respectively. Austrian and German banks take less in both operations.

Using the Kolari and Pynnönen (2010) test statistic to assess statistical significance over the first cash settlement leaves only the $CAAR$ of 2.3% in Spain over the window $[-5, 5]$ statistically different from zero at the level of 10%. The $CAAR$ of 16.0% in Portugal over the same window, however, has a p-value of 12.0%. Portuguese banks take 1.4 times as much LTRO liquidity as Austrian banks and have already 10.6 times as much outstanding prior to the three-year LTROs. At the same time, the only statistically significant cumulative abnormal return in non-peripheral countries is the one of 1.9% in Finland over the same window.

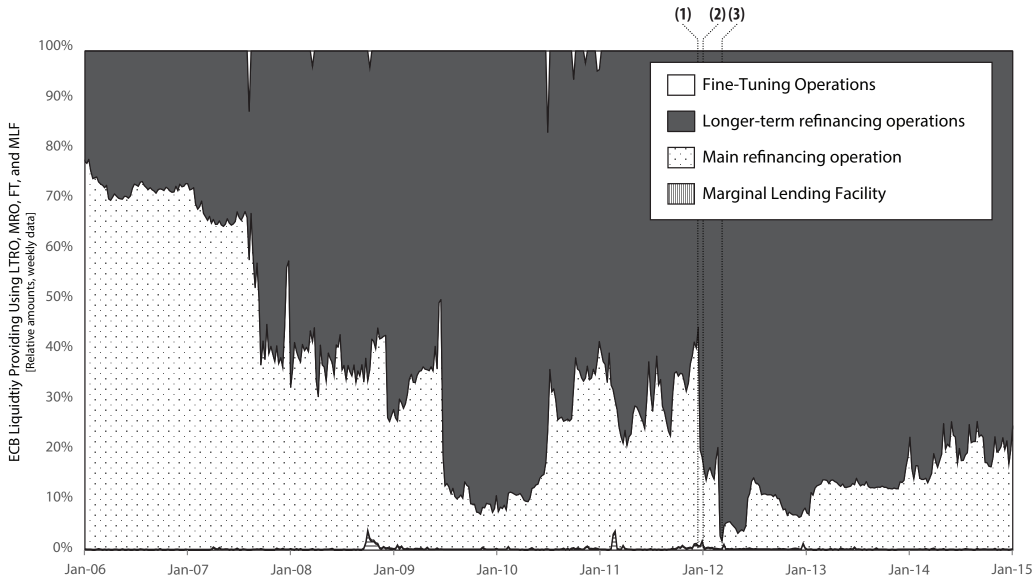
Using less conservative test statistics (Boehmer et al., 1991; Brown and Warner, 1980) renders *CAARs* more significant. The findings, however, remain qualitatively the same. *CAARs* in peripheral countries are higher than in non-peripheral countries. A number of robustness checks do not change them.

These results provide evidence that the three-year LTROs help in particular financially weaker Eurozone banks. This is in line with Nyborg (2017)'s argument that the three-year LTROs possess the features of an indirect bailout for banks in financially weaker Eurozone countries. The finding that bank *CAARs* are especially high in countries with large liquidity uptake strengthens Nyborg (2017)'s point further.

3.7 Figures



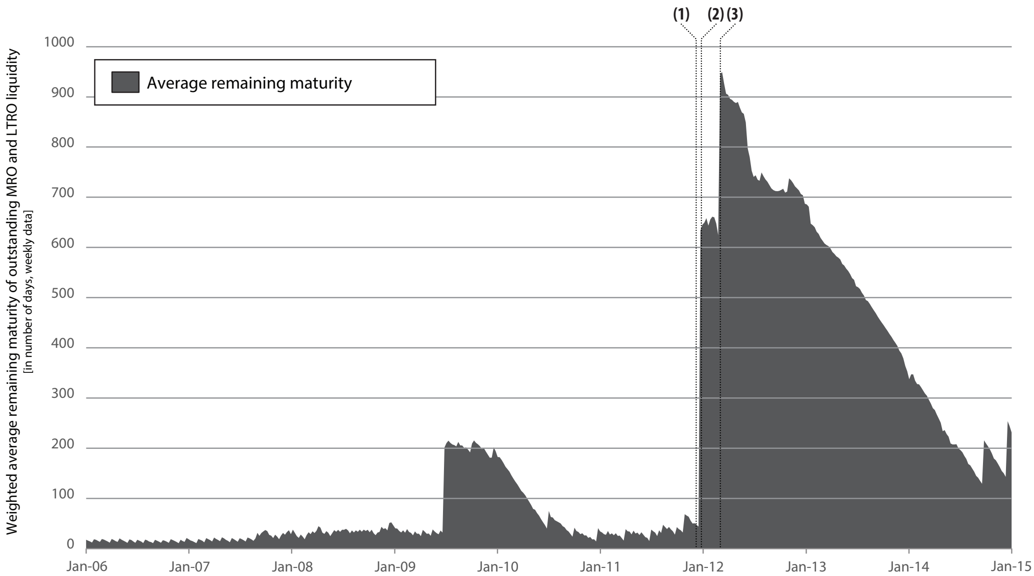
Panel A: Absolute Liquidity Provided Using LTRO, MRO against Deposit Facility



Panel B: Relative Liquidity Provided Using LTRO, MRO, FT, and MLF

Figure 3.1

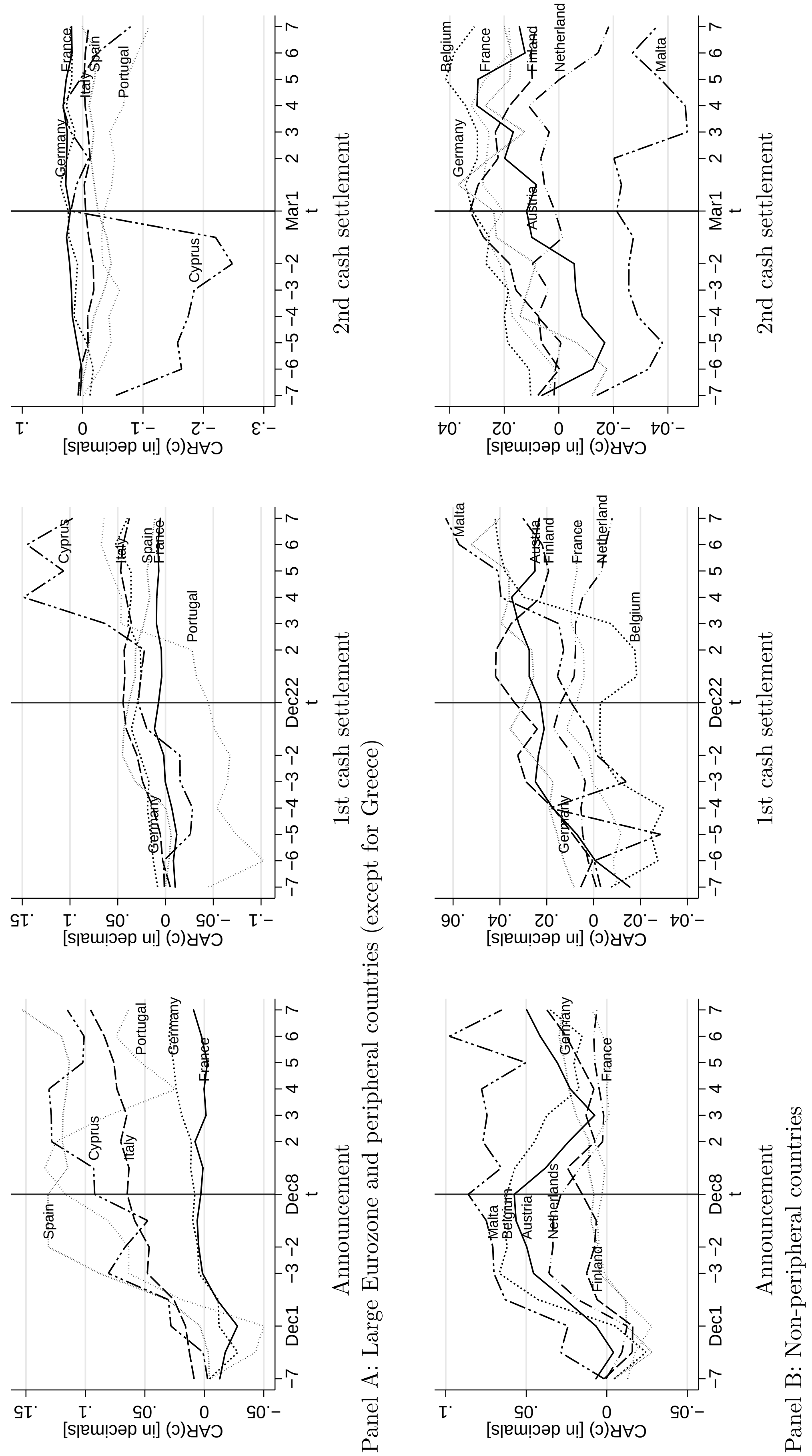
ECB Liquidity Uptakes from 2006 to 2014. This figure depicts the amounts of ECB liquidity uptakes from the beginning of 2006 to the end of 2014. Panel A shows the absolute amounts of liquidity provided using LTRO and MRO as compared to funds deposited at the ECB deposit facility. Panel B shows the relative amounts of LTRO, MRO, FT, and MLF over the same period. The vertical lines indicate our key events: (1) December 8, 2011: announcement of the three-year LTRO, (2) December 22, 2011: first settlement date, and (3) March 1, 2012: second settlement date. Source: ECB.



Average remaining maturity of credit on the ECB's balance sheet

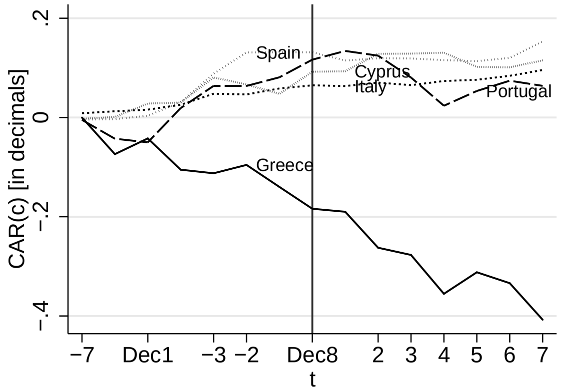
Figure 3.2

Relative Share of LTRO Liquidity Uptake. This figure depicts the weighted average remaining maturity of outstanding MRO and LTRO liquidity in number of days. The vertical lines indicate the same key events as in Figure 3.1. Source: ECB.

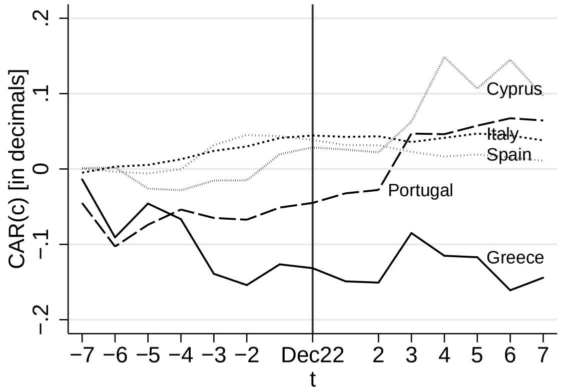


Panel A: Large Eurozone and peripheral countries (except for Greece)

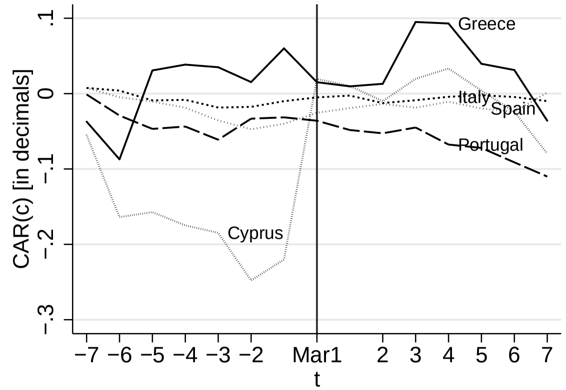
Panel B: Non-peripheral countries



Announcement



1st cash settlement



2nd cash settlement

Panel C: Peripheral countries

Figure 3.3

Average Cumulative Abnormal Returns on Bank Stocks by Country Using Country-level Market Indices. This figure is based on the bank stock sample and provides country-level averages of cumulative abnormal returns, CAR_c, across banks, CAR_i, for the three different events separately. CAR_i is the sum over abnormal returns for bank i, $AR_{i,t}$, over the event window $[-7, 7]$. $AR_{i,t}$ is estimated from the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event separately. $r_{m,t}$ is based on a country-level total market return index (for details see Section 3.3). The three columns of subplots represent the three events indicated by vertical lines in each subplot: announcement, 1st cash settlement, and 2nd cash settlement of the three-year LTROs on December 8, 2011, December 22, 2011, and March 1, 2012, respectively. The vertical line on December 1, 2011, in the first column of subplots, represents the ECB's first indication of large-scale help for banks. Panel A covers large Eurozone countries (Germany and France) as well as peripheral countries (except for Greece). Panels B and C cover non-peripheral and peripheral countries, respectively.

3.8 Tables

Table 3.1

Main Monetary Policy Operations of the ECB. This table lists the most important monetary policy instruments of the ECB divided into open market operations (OMO) and standing facilities (SF). Source: adapted from ECB (2011, p. 95).

Monetary policy operations	Type of transaction: Liquidity providing	Type of transaction: Liquidity absorbing	Maturity	Frequency	Procedure
Panel A: Open market operations (OMO)					
Main refinancing operations (MRO)	Reverse transactions	–	One week	Weekly	Standard tenders
Longer-term refinancing operations (LTRO)	Reverse transactions	–	Three months	Monthly	Standard tenders
Panel B: Standing facilities					
Marginal lending facility	Reverse transactions	–	Overnight	Access at the discretion of counterparties	
Deposit facility	–	Deposits	Overnight	Access at the discretion of counterparties	

Table 3.2

ECB Open Market Operations. This table shows the average allotted amounts in billion EUR in panel A, the average number of bidders in panel B, and the absolute number of ECB OMO MRO and LTRO transactions for the period 2000 – 2013 categorized by duration. Source: Woschitz (2017).

	MROs		LTROs				
	7d	14d	1m	3m	6m	12m	36m
Panel A: Number of Transactions per Year							
2000		51		12			
2001	2	52		12			
2002		53	1	11			
2003	3	52	1	11			
2004	43	9	1	11			
2005	52		2	11			
2006	52		1	11			
2007	51	1	1	15			
2008	53		5	18	5		
2009	52		14	22	12	3	
2010	52		13	11	2		
2011	52		13	11	1	1	1
2012	52		13	11			1
2013	53		14	10			
Panel B: Average Number of Bidders per Transaction							
2000		721.4		270.0			
2001	247.5	410.4		225.2			
2002		306.9	220.0	182.5			
2003	132.3	274.5	106.0	134.9			
2004	351.3	282.7	138.0	160.5			
2005	351.0		147.0	151.4			
2006	377.4		136.0	164.7			
2007	336.9	390.0	159.0	144.5			
2008	442.9		157.6	156.4	144.4		
2009	401.2		73.1	47.8	51.3	644.7	
2010	114.8		38.3	90.5	59.0		
2011	191.8		59.5	166.8	114.0	181.0	523.0
2012	94.7		27.8	42.3			800.0
2013	75.6		24.7	45.5			
Panel C: Average Alloted Amounts per Transaction [mill EUR]							
2000		79,961		17,500			
2001	63,000	79,060		20,000			
2002		66,477	20,000	17,273			
2003	53,667	98,303	15,000	15,000			
2004	244,082	107,184	25,000	25,000			
2005	290,144		30,000	28,864			
2006	307,087		40,000	40,000			
2007	255,186	348,607	50,000	52,232			
2008	201,113		75,073	54,934	35,928		
2009	149,753		53,675	14,723	11,132	204,806	
2010	133,831		38,462	39,712	26,772		
2011	158,968		72,475	66,489	49,752	56,934	489,191
2012	97,849		17,852	13,984			529,531
2013	108,040		5,456	7,400			

Table 3.3

ECB Liquidity Providing Allotments. This table shows the details of the announcement, allotment, and settlement of the 1-year and 3-year extraordinary longer-term refinancing operations (LTROs) in 2011/2012. Panel A gives the details of the announcement, allotment, and settlement details. On the allotment date participating banks hand in the amount, they would be willing to borrow, on the settlement date, the requested amount is paid out from the ECB to the counterparties. On the redemption date, the borrowed amount has to be redeemed. Panel B lists the total amounts outstanding from earlier MRO and LTRO transactions for the week preceding the settlement date. Panel C finally shows the overall net changes during the week of the settlement. A positive (negative) value for Δ MRO / LTRO lending means an increase (reduction) of the amount outstanding in MRO / LTRO financing. LTRO substitution finally gives the net substitution effect of MRO financing that has been replaced by LTRO financing. Source: ECB.

	1-year LTROs announced 06-Oct-2011		3-year LTROs announced 08-Dec-2011	
	#1	#2	#1	#2
Panel A: LTRO allotment / settlement / redemption details				
Allotment date	26-Oct-2011	21-Dec-2011	21-Dec-2011	29-Feb-2012
Settlement date	27-Oct-2011	22-Dec-2011	22-Dec-2011	1-Mar-2012
Redemption date	1-Nov-2012	31-Jan-2013	29-Jan-2015	26-Dec-2015
Maturity [days]	371	406	1,134	1,092
Alloted amount [mill EUR]	56,934	replaced	489,190	529,530
Number of counterparties	371	–	523	800
Panel B: Previous Weeks Amount Outstanding [mill EUR]				
LTRO lending	201,182		291,629	166,490
MRO lending	585,241	–	665,008	819,682
Panel C: Overall Net Change in Settlement Week [mill EUR]				
Δ LTRO lending	16,522		335,285	447,979
Δ MRO lending	(3,744)	–	(122,605)	(137,021)
LTRO substitution	(40,412)	–	(153,905)	(81,551)

Table 3.4

Estimates of Net Liquidity Uptake over the Three-Year LTRO Cash Settlements. This table shows estimates of liquidity uptake in MROs, LTROs, and the total by country for those countries whose national central banks provide separate figures on MROs and LTROs on their balances sheets. As different national central banks provide the figures in different formats, we proceed according to Woschitz (2017) to make the numbers comparable. Panel A provides outstanding liquidity end of October 2011 and liquidity uptake from the beginning of November 2011 to the end of January 2012 as well as from the beginning of February to the end of April 2012, two periods which span over the first and second three-year LTRO cash settlements, respectively. Numbers are in million EUR. Countries are sorted according to LTRO uptake in the period from November 2011 to January 2012. Panel B calculates the percentage change on outstanding liquidity end of October 2011 and January 2012. "(P)" indicates countries that are classified as peripheral countries. (*) indicates countries that our sample of bank stocks used in the event study later on does not cover. Our bank stock sample, however, additionally covers the Netherlands, Malta, and Cyprus (P). Source: Bruegel data (see Pisani-Ferry and Wolff, 2012).

Panel A: Estimates of absolute net liquidity uptake over 3y-LTRO implementations [in million EUR]

	Outstanding liquidity			Absolute net uptake over 1st 3y-LTRO			Absolute net uptake over 2nd 3y-LTRO		
	End of Oct-2011			Nov-2011 to Jan-2012			Feb-2012 to Apr-2012		
	MRO	LTRO	Total	MRO	LTRO	Total	MRO	LTRO	Total
Spain (P)	43,185	42,994	86,178	-36,740	111,983	75,243	-4,664	160,176	155,513
Italy (P)	46,821	61,164	107,985	4,083	94,191	98,274	-48,402	112,637	64,235
France	33,090	63,897	96,987	-31,400	68,558	37,158	-157	36,645	36,488
Germany	6,394	19,025	25,419	-3,185	24,186	21,001	-1,907	30,341	28,435
Belgium	11,579	6,650	18,229	-715	11,253	10,538	-10,699	21,893	11,194
Port. (P)	12,814	32,764	45,578	-4,792	5,432	640	-3,575	13,074	9,500
Austria	2,333	3,099	5,432	37	3,898	3,935	-2,282	8,741	6,460
Finland	0	105	105	5	2,201	2,206	-5	1,375	1,370
Luxemb.(*)	1,797	1,727	3,524	-278	1,528	1,251	-1,467	1,740	273
Slovenia(*)	4	625	629	52	1,058	1,110	-20	2,088	2,068
Ireland(*)	22,206	77,715	99,921	3,861	-5,341	-1,480	-19,225	6,702	-12,523
Greece (P)	8,886	66,858	75,744	6,054	-7,146	-1,092	19,375	-23,645	-4,269
Total	189,109	376,622	565,731	-63,017	311,799	248,782	-73,025	371,767	298,742

Panel B: Relative net liquidity uptake as a percentage of outstanding liquidity end of last period [as %]

	Relative net uptake over 1st 3y-LTRO			Relative net uptake over 2nd 3y-LTRO		
	Nov-2011 to Jan-2012 as of Oct-2011			Feb-2012 to Apr-2012 as of Jan-2011		
	MRO	LTRO	Total	MRO	LTRO	Total
Spain (P)	-85.1	260.5	87.3	-72.4	103.4	96.3
Italy (P)	8.7	154.0	91.0	-95.1	72.5	31.1
France	-94.9	107.3	38.3	-9.3	27.7	27.2
Germany	-49.8	127.1	82.6	-59.4	70.2	61.3
Belgium	-6.2	169.2	57.8	-98.5	122.3	38.9
Port. (P)	-37.4	16.6	1.4	-44.6	34.2	20.6
Austria	1.6	125.8	72.4	-96.3	124.9	69.0
Finland	-	2,096.2	2,101.0	-100.0	59.6	59.3
Luxemb.(*)	-15.4	88.5	35.5	-96.6	53.5	5.7
Slovenia(*)	1,300.0	169.3	176.5	-34.8	124.1	119.0
Ireland(*)	17.4	-6.9	-1.5	-73.8	9.3	-12.7
Greece (P)	68.1	-10.7	-1.4	129.7	-39.6	-5.7

Table 3.5

Descriptive Statistics. This table provides descriptive statistics (as percentage) and the number of observations by country. Panel A covers the bank equity return sample. Panel B calculates per country an equally-weighted portfolio of the bank equity returns from Panel A. Panel C provides statistics on the country-level market indices as well as the "STOXX Europe 600" index and Panel D on country-level bank indices. The sample spans 260 business days from March 15, 2011 (-192 days from the announcement of the three-year LTROs on December 8, 2011) to March 12, 2012 (+7 business days from the second three-year LTRO cash settlement on March 1, 2012). "(P)" indicates whether a country is classified as a peripheral country (the other countries are classified as non-peripheral).

Panel A: Bank equity sample by country

	Descriptive Statistics								Number of				Number of zero returns			
													obs.		$[-7, 7]$ day obs.	
Country	Mean in %	SD in %	SE in %	P25 in %	Med in %	P75 in %	Min in %	Max in %	banks	days	obs.	$[-7, 7]$ day obs.	count	%	count	%
Austria	-0.07	3.06	0.09	-1.43	0.00	1.34	-13.19	14.76	4	260	1,040	160	77	7.40	22	13.75
Belgium	-0.08	2.80	0.09	-1.31	-0.16	1.03	-13.17	16.46	4	260	1,040	160	27	2.60	4	2.50
Finland	-0.03	2.27	0.07	-1.30	0.00	1.19	-8.59	9.57	4	260	1,040	160	64	6.15	10	6.25
France	-0.08	2.34	0.03	-0.93	0.00	0.76	-16.23	22.54	18	260	4,680	720	353	7.54	60	8.33
Germany	-0.03	3.21	0.06	-1.41	0.00	1.27	-14.88	30.00	13	260	3,380	520	164	4.85	30	5.77
Malta	0.04	2.24	0.14	-0.76	0.05	0.82	-15.00	18.35	1	260	260	40	11	4.23	2	5.00
Netherl.	-0.09	2.49	0.07	-1.22	0.00	1.05	-10.25	11.49	5	260	1,300	200	42	3.23	8	4.00
Greece (P)	-0.37	7.35	0.46	-3.55	-0.55	2.20	-28.02	29.52	1	260	260	40	28	10.77	2	5.00
Italy (P)	-0.10	2.90	0.04	-1.49	-0.05	1.21	-17.27	33.17	26	260	6,760	1,040	351	5.19	69	6.63
Portugal (P)	-0.34	3.41	0.11	-2.22	-0.37	1.41	-13.55	20.55	4	260	1,040	160	59	5.67	11	6.88
Spain (P)	-0.18	2.92	0.06	-1.56	-0.03	1.10	-28.38	40.38	8	260	2,080	320	81	3.89	17	5.31
Cyprus (P)	-0.34	4.51	0.28	-2.78	-0.47	1.98	-16.38	25.76	1	260	260	40	15	5.77	5	12.50
Total	-0.10	2.93	0.02	-1.37	0.00	1.09	-28.38	40.38	89	260	23,140	3,560	1,272	5.50	240	6.74

Panel B: Equally weighted portfolio across bank equity by country

	Descriptive Statistics								Number of				Number of zero returns			
													obs.		$[-7, 7]$ day obs.	
Country	Mean in %	SD in %	SE in %	P25 in %	Med in %	P75 in %	Min in %	Max in %	banks	days	obs.	$[-7, 7]$ day obs.	count	%	count	%
Austria	-0.07	2.21	0.14	-1.19	-0.07	1.19	-6.22	7.26	1	260	260	40	6	2.31	2	5.00
Belgium	-0.08	1.90	0.12	-1.10	-0.03	0.82	-5.51	6.98	1	260	260	40	3	1.15	1	2.50
Finland	-0.03	1.84	0.11	-0.99	-0.16	1.01	-5.49	7.84	1	260	260	40	4	1.54	1	2.50
France	-0.08	1.31	0.08	-0.72	0.01	0.61	-4.76	5.92	1	260	260	40	3	1.15	1	2.50
Germany	-0.03	1.55	0.10	-0.76	0.04	0.85	-6.12	5.75	1	260	260	40	3	1.15	1	2.50
Malta	0.04	2.24	0.14	-0.76	0.05	0.82	-15.00	18.35	1	260	260	40	11	4.23	2	5.00
Netherl.	-0.09	1.79	0.11	-0.84	-0.03	0.81	-5.82	6.08	1	260	260	40	3	1.15	1	2.50
Greece (P)	-0.37	7.35	0.46	-3.55	-0.55	2.20	-28.02	29.52	1	260	260	40	28	10.77	2	5.00
Italy (P)	-0.10	1.76	0.11	-1.03	0.01	0.96	-5.66	4.32	1	260	260	40	4	1.54	1	2.50
Portugal (P)	-0.34	2.90	0.18	-1.83	-0.26	1.31	-10.63	11.63	1	260	260	40	3	1.15	1	2.50
Spain (P)	-0.18	2.04	0.13	-1.29	-0.06	0.87	-5.37	7.43	1	260	260	40	3	1.15	1	2.50
Cyprus (P)	-0.34	4.51	0.28	-2.78	-0.47	1.98	-16.38	25.76	1	260	260	40	15	5.77	5	12.50
Total	-0.14	3.08	0.06	-1.25	-0.05	0.96	-28.02	29.52	12	260	3,120	480	86	2.76	19	3.96

Table to be continued

Table 3.5 – continued

Panel C: Market index by country and index for total EU (EU STOXX 600)

	Descriptive Statistics								Number of				Number of zero returns			
													obs.		[−7, 7] day obs.	
Country	Mean in %	SD in %	SE in %	P25 in %	Med in %	P75 in %	Min in %	Max in %	banks	days	obs.	[−7, 7] day obs.	count	%	count	%
Austria	-0.07	1.89	0.12	-1.13	0.00	0.98	-6.11	5.81	1	260	260	40	12	4.62	3	7.50
Belgium	-0.03	1.55	0.10	-0.96	-0.02	0.82	-5.34	5.50	1	260	260	40	3	1.15	1	2.50
Finland	-0.03	1.80	0.11	-0.99	0.00	0.99	-5.94	5.60	1	260	260	40	7	2.69	2	5.00
France	-0.01	1.81	0.11	-0.89	0.00	1.03	-5.48	6.28	1	260	260	40	3	1.15	1	2.50
Germany	0.02	1.83	0.11	-0.87	0.00	0.95	-5.82	5.35	1	260	260	40	3	1.15	1	2.50
Malta	-0.06	0.89	0.06	-0.35	0.00	0.26	-6.63	4.52	1	260	260	40	30	11.54	7	17.50
Netherl.	-0.01	1.41	0.09	-0.81	0.00	0.85	-4.46	4.47	1	260	260	40	3	1.15	1	2.50
Greece (P)	-0.28	2.47	0.15	-1.75	-0.44	0.96	-6.92	14.37	1	260	260	40	9	3.46	2	5.00
Italy (P)	-0.07	2.09	0.13	-1.23	0.02	1.22	-6.80	5.49	1	260	260	40	4	1.54	1	2.50
Portugal (P)	-0.09	1.37	0.09	-0.95	-0.06	0.85	-5.02	3.70	1	260	260	40	3	1.15	1	2.50
Spain (P)	-0.05	1.74	0.11	-1.10	-0.04	0.94	-5.49	4.96	1	260	260	40	3	1.15	1	2.50
Cyprus (P)	-0.24	2.88	0.18	-2.07	-0.04	1.11	-10.71	17.62	1	260	260	40	4	1.54	1	2.50
Total	-0.08	1.88	0.03	-1.02	-0.01	0.86	-10.71	17.62	12	260	3,120	480	84	2.69	22	4.58
EU STOXX	0.01	1.39	0.09	-0.68	0.05	0.80	-4.77	4.37	1	260	260	40	3	1.15	1	2.50

Panel D: Bank index by country

	Descriptive Statistics								Number of				Number of zero returns			
													obs.		[−7, 7] day obs.	
Country	Mean in %	SD in %	SE in %	P25 in %	Med in %	P75 in %	Min in %	Max in %	banks	days	obs.	[−7, 7] day obs.	count	%	count	%
Austria	-0.17	3.53	0.22	-2.09	0.00	1.67	-9.71	11.49	1	260	260	40	12	4.62	3	7.50
Belgium	-0.18	4.27	0.26	-2.65	-0.28	2.34	-13.03	15.15	1	260	260	40	4	1.54	1	2.50
Finland	-0.01	2.19	0.14	-1.32	-0.05	1.28	-5.92	8.25	1	260	260	40	7	2.69	2	5.00
France	-0.11	3.92	0.24	-2.14	-0.11	2.05	-13.77	18.62	1	260	260	40	3	1.15	1	2.50
Germany	-0.05	3.31	0.21	-1.80	-0.12	1.59	-8.58	15.58	1	260	260	40	4	1.54	1	2.50
Malta	-0.03	0.79	0.05	-0.31	0.01	0.29	-6.41	3.48	1	260	260	40	3	1.15	0	0.00
Netherl.	-0.15	1.61	0.10	-0.95	0.00	0.72	-9.19	4.52	1	260	260	40	0	0.00	0	0.00
Greece (P)	-0.30	6.23	0.39	-3.53	-0.54	2.46	-20.39	29.39	1	260	260	40	10	3.85	2	5.00
Italy (P)	-0.17	3.47	0.22	-2.08	0.00	1.88	-11.63	8.85	1	260	260	40	4	1.54	1	2.50
Portugal (P)	-0.40	3.30	0.20	-2.18	-0.49	1.48	-12.16	14.38	1	260	260	40	4	1.54	2	5.00
Spain (P)	-0.07	2.30	0.14	-1.40	-0.03	1.25	-7.72	7.79	1	260	260	40	3	1.15	1	2.50
Cyprus (P)	-0.47	3.62	0.22	-2.50	-0.55	1.48	-11.07	16.49	1	260	260	40	1	0.38	1	2.50
Total	-0.18	3.47	0.06	-1.80	-0.08	1.35	-20.39	29.39	12	260	3,120	480	55	1.76	15	3.13

Table 3.6

Comparison of Abnormal Returns on Bank Stocks on Event versus Non-Event Days per Country. This table compares estimated abnormal returns on event to those on non-event days for the bank stock sample by country. Numbers are in percentage points. Countries are classified into non-peripheral and peripheral countries, as indicated in the table. Each of the three panels provides sample means, medians, standard deviations, and the number of observations on event days and non-event days. In each panel and for each country, the table shows two-sample t-tests for equal means, Kruskal-Wallis χ^2-tests for equal medians, and variance-ratio F-tests for equal variances comparing event versus non-event day abnormal returns. Abnormal returns are estimated with the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is based on a country-level total market return index (see Section 3.3). For each country in each panel the tests are based on a total of $[-192, 7] = 200$ days: $[-7, 7] = 15$ event days and $[-192, -8] = 185$ non-event days. In Panel A, $t = 0$ is the announcement of the three-year LTROs on December 8, 2011. In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). Test statistics and corresponding means, medians, and/or variances that are significant at the level of at least 10% are marked in bold. a, b, and c next to the test statistics denote significance at the levels of 1%, 5%, and 10%, respectively.

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel A: December 8, 2011 (announcement of three-year LTROs)													
Event days	Mean	0.332	0.234	0.248	0.060	0.183	0.435	0.041	**-2.717**	**0.638**	0.425	**1.021**	0.768
	Med	**0.184**	-0.037	**0.333**	0.040	0.091	0.344	-0.062	**-2.200**	**0.287**	-0.305	**0.474**	0.196
	SD	2.349	3.405	1.737	1.908	2.902	2.206	2.302	4.054	2.923	4.866	5.170	2.277
	Obs	60	60	60	270	195	15	75	15	390	60	120	15
Non-event days	Mean	-0.000	-0.000	0.000	0.000	0.000	-0.000	-0.000	**0.000**	**0.000**	-0.000	**0.000**	0.000
	Med	**0.011**	0.010	**0.014**	0.034	-0.071	-0.036	-0.008	**-0.209**	**-0.033**	-0.016	**-0.065**	0.128
	SD	1.863	1.854	1.528	1.635	2.712	2.490	1.552	4.826	2.017	2.395	1.819	2.532
	Obs	740	740	740	3,330	2,405	185	925	185	4,810	740	1,480	185
Event vs non-event days: Test for equal													
means	TT t-stat	-1.067	-0.526	-1.072	-0.504	-0.852	-0.727	-0.151	**2.458**^{b}	**-4.227**^{a}	-0.670	**-2.152**^{b}	-1.245
	TT p-val	0.290	0.601	0.288	0.615	0.395	0.477	0.880	0.025	0.000	0.505	0.033	0.230
meds	KW χ^2-stat	**2.922**^{c}	0.328	**2.764**^{c}	0.020	1.633	0.926	0.000	**6.123**^{b}	**14.450**^{a}	0.011	**23.059**^{a}	0.814
	KW p-val	0.087	0.567	0.096	0.888	0.201	0.336	0.993	0.013	0.000	0.918	0.000	0.367
vars	VR F-stat	**0.629**^{a}	**0.296**^{a}	0.774	**0.734**^{a}	0.874	1.273	**0.455**^{a}	1.417	**0.476**^{a}	**0.242**^{a}	**0.124**^{a}	1.236
	VR p-val	0.008	0.000	0.149	0.000	0.183	0.632	0.000	0.466	0.000	0.000	0.000	0.683

Table to be continued

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel B: December 22, 2011 (first three-year LTRO settlement)													
Event days	Mean	0.155	0.280	0.201	0.036	0.267	0.421	-0.053	-0.962	0.253	0.429	0.074	0.647
	Med	0.080	0.181	0.053	-0.013	0.075	0.369	-0.191	-1.367	0.012	0.354	-0.058	0.071
	SD	1.631	2.404	1.617	1.672	3.415	1.895	1.385	3.892	2.987	3.679	2.545	3.396
	Obs	60	60	60	270	195	15	75	15	390	60	120	15
Non-event days	Mean	0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	Med	0.003	0.013	-0.007	0.037	-0.068	-0.066	0.005	-0.090	-0.052	-0.066	-0.090	0.078
	SD	1.768	2.042	1.549	1.669	2.715	2.482	1.632	4.903	2.110	2.649	2.270	2.564
	Obs	740	740	740	3,330	2,405	185	925	185	4,810	740	1,480	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.701	-0.878	-0.930	-0.341	-1.063	-0.806	0.312	0.901	-1.640	-0.885	-0.307	-0.721
	TT p-val	0.485	0.383	0.356	0.733	0.289	0.431	0.755	0.379	0.102	0.379	0.759	0.482
meds	KW χ^2-stat	0.419	0.771	0.378	0.056	0.986	2.061	0.609	1.361	0.201	0.842	0.226	0.277
	KW p-val	0.518	0.380	0.539	0.813	0.321	0.151	0.435	0.243	0.654	0.359	0.635	0.599
vars	VR F-stat	1.175	**0.722**^{c}	0.917	0.997	**0.632**^{a}	1.716	**1.388**^{c}	1.587	**0.499**^{a}	**0.518**^{a}	**0.795**^{c}	**0.570**^{c}
	VR p-val	0.442	0.066	0.610	0.952	0.000	0.247	0.075	0.324	0.000	0.000	0.073	0.097
Panel C: March 1, 2012 (second three-year LTRO settlement)													
Event days	Mean	0.096	0.206	0.056	0.122	0.133	-0.240	-0.122	-0.240	-0.066	**-0.734**	0.009	-0.530
	Med	0.076	0.190	0.231	0.101	-0.016	-0.007	0.031	-0.552	-0.091	**-0.820**	-0.100	-1.757
	SD	1.535	1.467	1.185	1.491	3.113	1.080	1.307	5.100	1.994	1.944	2.993	7.716
	Obs	60	60	60	270	195	15	75	15	390	60	120	15
Non-event days	Mean	0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	**-0.000**	-0.000	-0.000
	Med	0.011	-0.070	-0.070	-0.023	-0.102	-0.118	-0.035	-0.229	-0.130	**-0.122**	-0.084	0.001
	SD	1.918	2.330	1.674	1.774	2.985	1.595	1.731	5.322	2.397	3.123	2.417	3.154
	Obs	740	740	740	3,330	2,405	185	925	185	4,810	740	1,480	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.459	-0.993	-0.339	-1.277	-0.578	0.793	0.756	0.175	0.621	**2.659**^{a}	-0.033	0.264
	TT p-val	0.648	0.324	0.736	0.203	0.564	0.437	0.451	0.864	0.535	0.009	0.974	0.795
meds	KW χ^2-stat	0.243	2.206	0.321	1.682	0.144	0.030	0.118	0.575	0.005	**4.898**^{b}	0.001	2.480
	KW p-val	0.622	0.137	0.571	0.195	0.704	0.862	0.731	0.448	0.945	0.027	0.973	0.115
vars	VR F-stat	**1.560**^{b}	**2.524**^{a}	**1.995**^{a}	**1.416**^{a}	0.919	**2.182**^{c}	**1.756**^{a}	1.089	**1.445**^{a}	**2.581**^{a}	**0.652**^{a}	**0.167**^{a}
	VR p-val	0.033	0.000	0.001	0.000	0.403	0.096	0.003	0.919	0.000	0.000	0.001	0.000

Table 3.7

Cumulative Average Abnormal Returns on Bank Stocks by Country Assessed with Brown and Warner (1980)'s Test Statistic. This table provides CAR_c for seven different windows and the three events, as indicated in the table, based on the bank stock sample by country. Numbers are given in decimals. In Panel A, $t = 0$ is the announcement of the three-year LTROs (December 8, 2011). In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). CAR_c is calculated as an average of CAR_i across banks within a country. CAR_i for each bank is calculated as the sum of $AR_{i,t}$ over the respective time window. Abnormal returns are estimated with the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is based on a country-level total market return index (see Section 3.3). Significance is evaluated using the test statistic proposed by Brown and Warner (1980) which is presented in brackets underneath the CAR_c. a, b, and c next to the CAR_c denote significance at the levels of 1%, 5%, and 10%, respectively.

	Non-peripheral countries							Peripheral countries				
	Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
# of banks	4	4	4	18	13	1	5	1	26	4	8	1
Panel A: December 8, 2011 (announcement of three-year LTROs)												
$[0, 1]$	-0.018	-0.007	0.018	-0.005	0.002	-0.009	-0.017	-0.050	0.005	**0.053**^{b}	-0.017	0.046
	(-1.40)	(-0.50)	(1.40)	(-0.56)	(0.11)	(-0.26)	(-1.56)	(-0.73)	(0.54)	(2.04)	(-1.48)	(1.26)
$[0, 3]$	**-0.049**^{a}	-0.027	0.006	-0.007	0.009	-0.000	**-0.032**^{b}	-0.137	0.007	-0.000	-0.012	0.081
	(-2.64)	(-1.37)	(0.36)	(-0.61)	(0.43)	(-0.01)	(-2.04)	(-1.41)	(0.53)	(-0.01)	(-0.79)	(1.59)
$[-1, 1]$	-0.012	-0.005	0.017	-0.004	0.006	-0.005	-0.017	-0.094	0.017	**0.071**^{b}	-0.016	0.026
	(-0.73)	(-0.28)	(1.07)	(-0.34)	(0.33)	(-0.12)	(-1.27)	(-1.12)	(1.55)	(2.21)	(-1.18)	(0.60)
$[-1, 3]$	**-0.042**^{b}	-0.025	0.005	-0.006	0.014	0.004	**-0.031**^{c}	**-0.181**^{c}	0.019	0.017	-0.012	0.062
	(-2.04)	(-1.12)	(0.26)	(-0.45)	(0.57)	(0.06)	(-1.82)	(-1.67)	(1.33)	(0.41)	(-0.68)	(1.09)
$[-3, 3]$	-0.018	-0.005	0.007	0.009	0.031	0.011	-0.016	-0.172	**0.040**^{b}	0.062	**0.088**^{a}	0.099
	(-0.74)	(-0.21)	(0.29)	(0.57)	(1.08)	(0.17)	(-0.78)	(-1.33)	(2.37)	(1.26)	(4.19)	(1.46)
$[-5, 5]$	0.035	0.045	0.032	0.015	0.054	0.022	0.017	-0.238	**0.063**^{a}	0.096	**0.117**^{a}	0.101
	(1.14)	(1.38)	(1.08)	(0.74)	(1.52)	(0.26)	(0.66)	(-1.48)	(3.04)	(1.57)	(4.44)	(1.19)
$[-7, 7]$	0.050	0.035	0.037	0.009	0.027	0.065	0.006	**-0.408**^{b}	**0.096**^{a}	0.064	**0.153**^{a}	0.115
	(1.39)	(0.93)	(1.06)	(0.38)	(0.66)	(0.67)	(0.21)	(-2.16)	(3.92)	(0.89)	(4.98)	(1.17)

Table to be continued

Table 3.7 – continued

	Non-peripheral countries							Peripheral countries				
	Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
# of banks	4	4	4	18	13	1	5	1	26	4	8	1
Panel B: December 22, 2011 (first three-year LTRO settlement)												
$[0, 1]$	0.006	-0.016	0.018	-0.008	-0.010	0.013	-0.009	-0.023	0.001	0.019	-0.012	0.006
	(0.50)	(-1.04)	(1.35)	(-0.85)	(-0.67)	(0.37)	(-0.78)	(-0.32)	(0.16)	(0.68)	(-0.85)	(0.17)
$[0, 3]$	0.011	-0.005	0.011	-0.002	0.004	0.013	-0.009	0.042	-0.005	**0.098**[b]	-0.021	0.043
	(0.60)	(-0.22)	(0.60)	(-0.16)	(0.18)	(0.25)	(-0.58)	(0.42)	(-0.40)	(2.48)	(-1.06)	(0.84)
$[-1, 1]$	0.004	-0.015	0.009	0.002	-0.001	0.017	-0.000	0.005	0.013	0.035	-0.013	0.041
	(0.25)	(-0.83)	(0.59)	(0.19)	(-0.06)	(0.39)	(-0.03)	(0.06)	(1.11)	(1.02)	(-0.79)	(0.91)
$[-1, 3]$	0.008	-0.004	0.003	0.008	0.013	0.016	-0.001	0.069	0.006	**0.114**[b]	-0.022	0.078
	(0.42)	(-0.19)	(0.13)	(0.54)	(0.54)	(0.29)	(-0.06)	(0.62)	(0.40)	(2.58)	(-1.02)	(1.35)
$[-3, 3]$	0.015	0.022	0.018	0.016	0.020	-0.004	0.002	-0.018	0.023	**0.101**[c]	0.023	0.091
	(0.61)	(0.79)	(0.73)	(0.96)	(0.73)	(-0.06)	(0.11)	(-0.14)	(1.30)	(1.92)	(0.89)	(1.33)
$[-5, 5]$	0.026	**0.065**[c]	0.019	0.015	0.023	0.041	-0.006	-0.026	**0.044**[b]	**0.160**[b]	0.023	0.105
	(0.86)	(1.84)	(0.61)	(0.73)	(0.67)	(0.50)	(-0.22)	(-0.16)	(2.00)	(2.44)	(0.70)	(1.22)
$[-7, 7]$	0.023	0.042	0.030	0.005	0.040	0.063	-0.008	-0.144	0.038	0.064	0.011	0.097
	(0.66)	(1.01)	(0.84)	(0.22)	(0.98)	(0.65)	(-0.25)	(-0.75)	(1.48)	(0.84)	(0.29)	(0.97)
Panel C: March 1, 2012 (second three-year LTRO settlement)												
$[0, 1]$	-0.002	0.009	0.002	0.001	0.014	0.004	0.007	-0.050	0.007	-0.017	0.021	**0.230**[a]
	(-0.12)	(0.51)	(0.14)	(0.13)	(0.88)	(0.19)	(0.55)	(-0.66)	(0.67)	(-0.49)	(1.43)	(5.12)
$[0, 3]$	0.007	0.004	-0.004	-0.001	-0.010	-0.020	0.005	0.035	0.001	-0.013	0.021	**0.240**[a]
	(0.36)	(0.18)	(-0.22)	(-0.08)	(-0.46)	(-0.61)	(0.29)	(0.33)	(0.08)	(-0.28)	(1.04)	(3.77)
$[-1, 1]$	0.014	0.008	0.012	0.006	0.028	0.003	-0.004	-0.006	0.015	-0.015	0.028	**0.258**[a]
	(0.84)	(0.36)	(0.68)	(0.53)	(1.46)	(0.10)	(-0.30)	(-0.06)	(1.11)	(-0.36)	(1.58)	(4.68)
$[-1, 3]$	0.022	0.003	0.005	0.004	0.004	-0.021	-0.006	0.080	0.009	-0.012	0.029	**0.268**[a]
	(1.04)	(0.11)	(0.24)	(0.26)	(0.16)	(-0.60)	(-0.32)	(0.66)	(0.50)	(-0.22)	(1.25)	(3.76)
$[-3, 3]$	0.025	0.010	0.016	0.008	-0.002	-0.018	-0.004	0.057	-0.001	-0.001	0.000	**0.194**[b]
	(1.00)	(0.30)	(0.61)	(0.45)	(-0.06)	(-0.43)	(-0.19)	(0.40)	(-0.03)	(-0.02)	(0.00)	(2.31)
$[-5, 5]$	0.042	0.031	0.010	0.026	0.036	-0.004	-0.002	0.127	-0.006	-0.043	-0.015	0.168
	(1.32)	(0.75)	(0.31)	(1.10)	(0.96)	(-0.08)	(-0.05)	(0.71)	(-0.24)	(-0.53)	(-0.44)	(1.59)
$[-7, 7]$	0.014	0.031	0.008	0.018	0.020	-0.036	-0.018	-0.036	-0.010	-0.110	0.001	-0.079
	(0.39)	(0.65)	(0.22)	(0.67)	(0.46)	(-0.58)	(-0.54)	(-0.17)	(-0.33)	(-1.17)	(0.04)	(-0.65)

Table 3.8

Cumulative Average Abnormal Returns on Bank Stocks by Country Assessed with Kolari and Pynnönen (2010)'s Test Statistic. This table provides CAR_c for seven different windows and the three events, as indicated in the table, based on the bank stock sample for sample countries with more than one bank. Numbers are given in decimals. In Panel A, $t = 0$ is the announcement of the three-year LTROs (December 8, 2011). In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). CAR_c is calculated as an average of CAR_i across banks within a country. CAR_i for each bank is calculated as the sum of $AR_{i,t}$ over the respective time window. Abnormal returns are estimated with the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is based on a country-level total market return index (see Section 3.3). Significance is evaluated using both the test statistic proposed by Boehmer et al. (1991) presented in brackets underneath the CAR_c, which controls for event-induced changes in variance, and Kolari and Pynnönen (2010) presented in square brackets underneath Boehmer et al. (1991)'s test statistic, which controls for both event-induced changes in variance and cross-correlation. a, b, and c next to the CAR_c denote significance at the levels of 1%, 5%, and 10%, respectively, with the Boehmer et al. (1991) test statistic and, in square brackets, the Kolari and Pynnönen (2010) test statistic.

	Non-peripheral countries						Peripheral countries		
	Austria	Belgium	Finland	France	Germany	Netherl.	Italy	Portugal	Spain
# of banks	4	4	4	18	13	5	26	4	8
Panel A: December 8, 2011 (announcement of three-year LTROs)									
$[0, 1]$	**-0.018**$^{c,[\cdot]}$	-0.007	**0.018**$^{b,[\cdot]}$	-0.005	0.002	-0.017	0.005	0.053	-0.017
	(-1.70)	(-1.53)	(2.33)	(-0.85)	(0.46)	(-1.32)	(0.72)	(1.22)	(0.29)
	[-1.51]	[-1.15]	[1.51]	[-0.47]	[0.28]	[-1.08]	[0.42]	[0.53]	[0.16]
$[0, 3]$	**-0.049**$^{c,[c]}$	**-0.027**$^{a,[a]}$	0.006	-0.007	0.009	**-0.032**$^{c,[\cdot]}$	0.007	-0.000	-0.012
	(-1.90)	(-3.96)	(0.84)	(-0.62)	(0.86)	(-1.85)	(0.81)	(0.52)	(0.34)
	[-1.69]	[-2.98]	[0.55]	[-0.34]	[0.52]	[-1.53]	[0.48]	[0.22]	[0.18]
$[-1, 1]$	-0.012	-0.005	0.017	-0.004	0.006	-0.017	**0.017**$^{c,[\cdot]}$	0.071	-0.016
	(-1.03)	(-0.39)	(0.81)	(-0.19)	(1.26)	(-0.65)	(1.73)	(1.08)	(0.39)
	[-0.92]	[-0.29]	[0.52]	[-0.11]	[0.76]	[-0.54]	[1.01]	[0.47]	[0.21]
$[-1, 3]$	**-0.042**$^{b,[b]}$	-0.025	0.005	-0.006	0.014	-0.031	**0.019**$^{c,[\cdot]}$	0.017	-0.012
	(-2.51)	(-0.97)	(0.28)	(-0.17)	(1.47)	(-0.91)	(1.69)	(0.58)	(0.41)
	[-2.23]	[-0.73]	[0.18]	[-0.09]	[0.89]	[-0.75]	[0.99]	[0.25]	[0.22]
$[-3, 3]$	-0.018	-0.005	0.007	**0.009**$^{a,[c]}$	**0.031**$^{b,[\cdot]}$	-0.016	**0.040**$^{a,[\cdot]}$	0.062	**0.088**$^{b,[\cdot]}$
	(-0.02)	(-0.01)	(1.22)	(3.25)	(2.22)	(0.28)	(2.71)	(0.85)	(2.08)
	[-0.02]	[-0.01]	[0.79]	[1.79]	[1.34]	[0.23]	[1.59]	[0.37]	[1.12]
$[-5, 5]$	0.035	0.045	**0.032**$^{b,[c]}$	0.015	**0.054**$^{a,[b]}$	**0.017**$^{b,[c]}$	**0.063**$^{a,[\cdot]}$	**0.096**$^{c,[\cdot]}$	**0.117**$^{a,[c]}$
	(1.50)	(0.60)	(2.58)	(1.29)	(3.35)	(2.24)	(2.71)	(1.87)	(3.33)
	[1.33]	[0.45]	[1.67]	[0.71]	[2.02]	[1.85]	[1.59]	[0.81]	[1.78]
$[-7, 7]$	0.050	0.035	0.037	0.009	0.027	0.006	**0.096**$^{b,[\cdot]}$	0.064	**0.153**$^{b,[\cdot]}$
	(1.52)	(0.38)	(0.99)	(-1.50)	(1.01)	(0.46)	(2.60)	(0.73)	(2.60)
	[1.35]	[0.28]	[0.64]	[-0.83]	[0.61]	[0.38]	[1.53]	[0.32]	[1.40]

Table to be continued

Table 3.8 – continued

	Non-peripheral countries						Peripheral countries		
	Austria	Belgium	Finland	France	Germany	Netherl.	Italy	Portugal	Spain
# of banks	4	4	4	18	13	5	26	4	8
Panel B: December 22, 2011 (first three-year LTRO cash settlement)									
$[0,1]$	0.006	-0.016	0.018	-0.008	-0.010	-0.009	0.001	0.019	-0.012
	(0.31)	(-0.26)	(0.73)	(-0.69)	(-1.38)	(-1.46)	(0.33)	(0.61)	(-1.46)
	[0.32]	[-0.18]	[0.50]	[-0.39]	[-0.86]	[-1.23]	[0.19]	[0.26]	[-0.84]
$[0,3]$	0.011	-0.005	0.011	-0.002	0.004	**-0.009**$^{c,[\cdot]}$	-0.005	0.098	**-0.021**$^{c,[\cdot]}$
	(0.52)	(0.18)	(0.74)	(-0.12)	(-0.41)	(-1.86)	(-0.53)	(1.54)	(-1.88)
	[0.53]	[0.13]	[0.51]	[-0.07]	[-0.26]	[-1.57]	[-0.30]	[0.67]	[-1.09]
$[-1,1]$	0.004	-0.015	0.009	0.002	-0.001	-0.000	0.013	0.035	-0.013
	(-0.06)	(-1.11)	(0.22)	(1.26)	(0.24)	(0.34)	(0.78)	(1.03)	(-1.12)
	[-0.06]	[-0.77]	[0.15]	[0.72]	[0.15]	[0.29]	[0.45]	[0.45]	[-0.64]
$[-1,3]$	0.008	-0.004	0.003	**0.008**$^{c,[\cdot]}$	0.013	-0.001	0.006	**0.114**$^{c,[\cdot]}$	-0.022
	(0.10)	(-0.31)	(0.00)	(1.75)	(0.57)	(0.41)	(0.41)	(1.75)	(-1.39)
	[0.10]	[-0.22]	[0.00]	[0.99]	[0.35]	[0.35]	[0.24]	[0.76]	[-0.80]
$[-3,3]$	0.015	**0.022**$^{c,[\cdot]}$	0.018	**0.016**$^{c,[\cdot]}$	0.020	0.002	0.023	0.101	**0.023**$^{c,[\cdot]}$
	(1.52)	(1.94)	(1.27)	(1.82)	(1.47)	(0.06)	(1.64)	(1.26)	(1.95)
	[1.55]	[1.34]	[0.87]	[1.03]	[0.92]	[0.05]	[0.94]	[0.55]	[1.13]
$[-5,5]$	0.026	0.065	**0.019**$^{a,[b]}$	0.015	**0.023**$^{b,[\cdot]}$	-0.006	**0.044**$^{c,[\cdot]}$	**0.160**$^{a,[\cdot]}$	**0.023**$^{a,[c]}$
	(1.40)	(1.45)	(2.94)	(1.12)	(2.13)	(0.10)	(1.75)	(3.61)	(2.99)
	[1.43]	[1.01]	[2.03]	[0.64]	[1.33]	[0.08]	[1.00]	[1.56]	[1.73]
$[-7,7]$	0.023	0.042	0.030	0.005	**0.040**$^{c,[\cdot]}$	-0.008	0.038	0.064	**0.011**$^{c,[\cdot]}$
	(1.27)	(0.38)	(1.19)	(0.22)	(1.88)	(0.09)	(1.50)	(-0.84)	(1.81)
	[1.30]	[0.26]	[0.82]	[0.12]	[1.17]	[0.07]	[0.86]	[-0.37]	[1.04]

Table to be continued

Table 3.8 – continued

	Non-peripheral countries						Peripheral countries		
	Austria	Belgium	Finland	France	Germany	Netherl.	Italy	Portugal	Spain
# of banks	4	4	4	18	13	5	26	4	8
Panel C: March 1, 2012 (second three-year LTRO cash settlement)									
$[0,1]$	-0.002	**0.009**$^{b,[b]}$	0.002	0.001	0.014	0.007	0.007	-0.017	0.021
	(0.15)	(2.34)	(0.65)	(-0.35)	(1.19)	(1.11)	(1.30)	(-1.32)	(0.22)
	[0.12]	[2.00]	[0.46]	[-0.18]	[0.75]	[0.80]	[0.71]	[-0.55]	[0.13]
$[0,3]$	0.007	0.004	-0.004	-0.001	-0.010	0.005	0.001	-0.013	0.021
	(0.67)	(1.57)	(0.17)	(-0.35)	(-0.71)	(1.23)	(0.31)	(-1.02)	(-0.23)
	[0.54]	[1.34]	[0.12]	[-0.18]	[-0.44]	[0.89]	[0.17]	[-0.43]	[-0.13]
$[-1,1]$	0.014	0.008	0.012	0.006	**0.028**$^{a,[c]}$	-0.004	**0.015**$^{b,[\cdot]}$	-0.015	0.028
	(1.06)	(0.96)	(1.44)	(1.64)	(2.73)	(-0.84)	(2.25)	(-1.37)	(1.32)
	[0.86]	[0.82]	[1.02]	[0.84]	[1.72]	[-0.60]	[1.24]	[-0.57]	[0.77]
$[-1,3]$	0.022	0.003	0.005	0.004	0.004	-0.006	0.009	-0.012	0.029
	(1.53)	(0.56)	(0.98)	(1.30)	(1.48)	(-0.61)	(1.40)	(-0.84)	(0.79)
	[1.24]	[0.48]	[0.69]	[0.67]	[0.93]	[-0.44]	[0.77]	[-0.35]	[0.46]
$[-3,3]$	**0.025**$^{a,[a]}$	0.010	**0.016**$^{a,[a]}$	**0.008**$^{b,[\cdot]}$	-0.002	-0.004	-0.001	-0.001	0.000
	(3.47)	(1.28)	(3.86)	(2.05)	(0.53)	(-0.48)	(-0.98)	(-0.31)	(-1.19)
	[2.81]	[1.09]	[2.72]	[1.05]	[0.33]	[-0.35]	[-0.54]	[-0.13]	[-0.69]
$[-5,5]$	**0.042**$^{b,[c]}$	**0.031**$^{a,[a]}$	**0.010**$^{a,[a]}$	**0.026**$^{b,[\cdot]}$	0.036	-0.002	**-0.006**$^{c,[\cdot]}$	**-0.043**$^{b,[\cdot]}$	-0.015
	(2.32)	(3.08)	(5.63)	(2.44)	(1.51)	(0.29)	(-1.79)	(-2.14)	(-0.70)
	[1.87]	[2.63]	[3.97]	[1.25]	[0.95]	[0.21]	[-0.99]	[-0.89]	[-0.41]
$[-7,7]$	0.014	**0.031**$^{b,[b]}$	**0.008**$^{c,[\cdot]}$	**0.018**$^{b,[\cdot]}$	0.020	-0.018	-0.010	**-0.110**$^{a,[b]}$	0.001
	(0.90)	(2.57)	(1.81)	(2.00)	(0.07)	(-0.29)	(-0.42)	(-5.01)	(-0.80)
	[0.73]	[2.20]	[1.28]	[1.03]	[0.04]	[-0.21]	[-0.23]	[-2.10]	[-0.47]

Part III

Appendices

A Appendix: Chapter 1

A.1 Experiment Instructions

Figure 1.2 shows the flow chart of the experiment with the ordering of the different treatments. Questions in the priming treatments are identical to Cohn et al. (2015, Online Appendix). Risk aversion elicitation is based on the ten paired lorry-choice with low payoffs as proposed by (Holt and Laury, 2002, p. 1645). Questions about the experiment have been ordered randomly to avoid order effects. All questions were asked in German.

A.1.1 Introduction

Welcome!

You successfully logged in for the experiment. Please take the following points into consideration before you start with the experiment:

- It is vital that you take part in the experiment all alone and that you do not talk to other students about how you played
- During the experiment you will receive video instructions: watch these instructions in full length before you start the experiment
- Duration of the experiment: app. 45 minutes
- Examination points: 5 points (you receive these points irrespective of how "well" you play)
- Please post a message in the OLAT forum in case of technical problems while playing the experiment

Now watch the following video instruction: SWITCHTube Video

Welcome in the experiment with chocolate. My name is René Hegglin and I will guide you through this experiment. The experiment is a regular part of the lecture "Banking" and gives you points for the exam. However, it is not only about points for the exam. You will become part of a form of teaching that is almost unused at the University of Zurich: the main goal is the implementation of an internet based classroom experiment. This, however, is only the official goal. The effective goal is to gain as many chocolate pralines as possible. During the experiment you gather Taler that may be converted into chocolate pralines afterwards. You may well be greedy since the chocolate is donated by the FinanceClub of UZH. Thanks for that. Per six Taler you earn, you will get one praline paid out.

During the experiment we investigate the investment behavior in different situations. It is imminently important that you focus on the specific task because you want to earn as many Taler as possible. It is also important to notice that during the complete experiment you are anonymous and all the data generated in the experiment is treated completely confidential, and will only be analyzed in an anonymous form. To avoid that your colleagues are influenced you should not talk to them about how you played the experiment.
Now the experiment starts. You may begin by clicking the "start" button below.

A.1.2 Priming Treatments

Priming Start Questionnaire

Investment behavior and power of concentration

- This introductory part of the experiment investigates investment behavior and the individual power of concentration.
- This part is split in six separate steps.
- To generate a complete overall picture, you are kindly asked to fill in all questions.
- **Important:** All answers are treated completely confidentially and are only analyzed in an anonymous form.

Q1. How often do you make investment decisions (e.g. purchase / selling of shares)?

◯ never
◯ once a year
◯ once every half-year
◯ every 3 months
◯ once a month
◯ every 2 weeks
◯ once a week
◯ daily

Q2. Which one of the following statements best describes your investment behavior?

◯ I make my own investment decisions based on information which I collect myself
◯ I follow the advice of my financial advisor but I take the final decision
◯ I leave the decisions to my financial advisor but I want to be kept up to date about it
◯ I leave the decision to my financial advisor and I do not want to know all the details about it

Q3. Do you think that one can trust most financial advisors or not?

One can trust **few**	-3	-2	-1	0	1	2	3	One can trust **most**
financial advisors	◯	◯	◯	◯	◯	◯	◯	financial advisors

Q4. Concerning financial decisions: To what extent are you willing to forgo something in order to benefit from it in the future?

Not at all willing	0	1	2	3	4	5	6	7	8	9	10	**Very** willing to
to forego something	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	forego something

Boom Priming

Imagine you are in a situation of a stock market boom like illustrated below. Assume you are an investor with a large investment volume. Your expectation is that the positive stock market boom continues in a similar way like indicated by the arrow in the illustration.

Shares: For such a situation would you rather **buy** or **sell** shares? Please give a brief explanation.

```
long text field
```

Gold and other precious metals: For such a situation would you rather **buy** or **sell** gold and other precious metals? Please give a brief explanation.

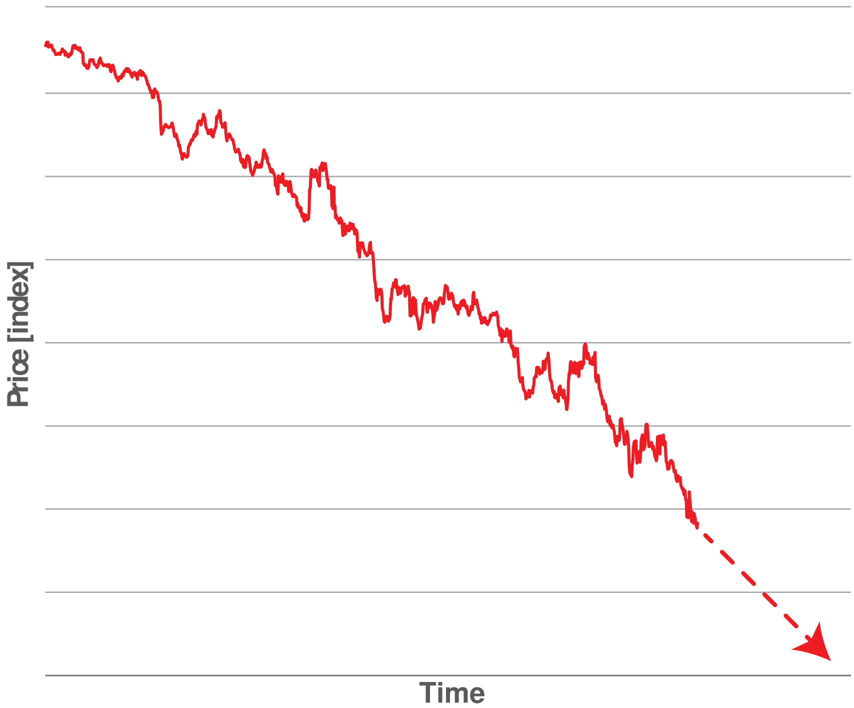
```
long text field
```

Real Estate: For such a situation would you rather **buy** or **sell** real estate? Please give a brief explanation.

```
long text field
```

Bust Priming

Imagine you are in a situation of a stock market crash like illustrated below. Assume you are an investor with a large investment volume. Your expectation is that the negative stock market crash continues in a similar way like indicated by the arrow in the illustration.



Shares: For such a situation would you rather **buy** or **sell** shares? Please give a brief explanation.

`long text field`

Gold and other precious metals: For such a situation would you rather **buy** or **sell** gold and other precious metals? Please give a brief explanation.

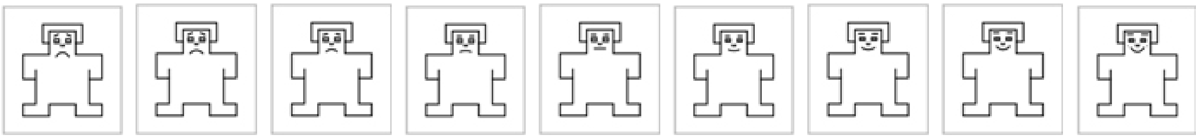
`long text field`

Real Estate: For such a situation would you rather **buy** or **sell** real estate? Please give a brief explanation.

`long text field`

Priming End Questionnaire

How well are you feeling at the moment?



To what extent are you experiencing the emotion "fear" at the moment?

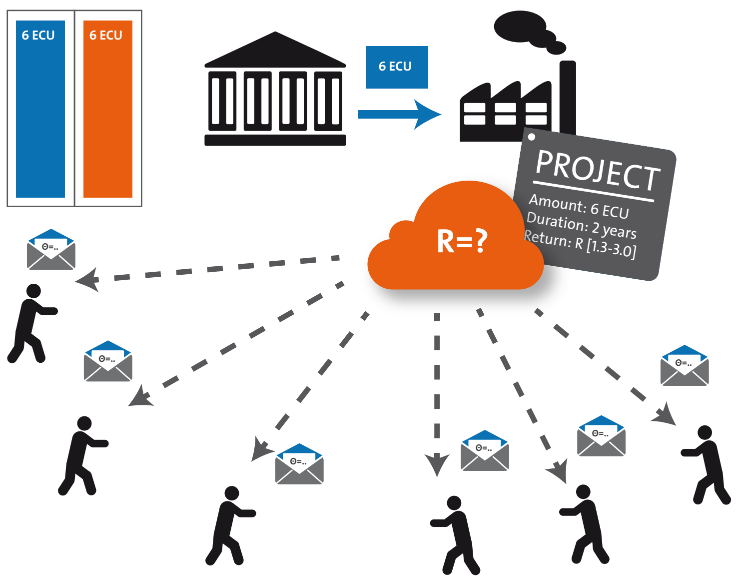
not at all	0	1	2	3	4	5	6	a lot

A.1.3 Bank Run Treatment

The Bank Run Treatment consists of an instruction part and 20 periods of two stages. Instructions were given in a video with oral explanations.

Instructions

Welcome to the main part of the experiment. In this video I explain the rules of the game that follows. In this part you assume the role of a depositor of a bank. We will play 20 periods. In each period you have to decide whether you want to withdraw your money early or late. However, in the decision situation you are not alone. At the beginning of every round you are randomly assigned to a group of six depositors together with five other depositors. The decisions of the other five depositors are real decisions that had been recorded in an earlier study.
All six depositors deposit their money with a single bank. It is important to notice that after each round the groups are dissolved and will be randomly reshuffled with new depositors in the next round. Thus, in every round you will be in a new group with new players and your reputation, how you played i earlier stages, does not play a role.
A round always consists of three sub periods. At time $t = 0$ all of the six depositors deposit one Taler with the bank. At time $t = 0$ the bank thus has six Taler. The bank invests these six Taler in a long-term project with a duration of two years. At time $t = 2$ the project will be liquidated and return is distributed evenly among all depositors. However, if a depositor wants to withdraw at time $t = 1$ the bank has to divest a part of the project early. The bank gives 1.5 Taler to the depositor. It is important to notice that at time $t = 0$ neither the bank nor any investor knows the true return of the project, i.e., the exact value of R is unknown. It is only known that the return is uniformly distributed in the range of 1.3 and 3.0.



It is obvious that at time $t = 1$ every depositor would like to know the approximate return R. Unfortunately, this information is not given. All that the depositors get is a private noisy signal, θ, about the approximate value of the return of the project. One can imagine that depositors have read in the newspaper how well the project does and how large the return R might be. Note that the signal that every depositor receives is specific, i.e., every depositor receives a signal that can be higher or lower than the signals of other depositors in the group.

At time $t = 1$, every depositor has to decide whether he wants to withdraw early. He knows that his private signal is noisy. The true return lies in the interval of plus minus 0.1 of the signal θ. Using this information, every depositor decides individually to withdraw early in $t = 1$ or to wait until the end of the two years.

If we assume that two depositors decide to withdraw early, i.e., two depositors go to the bank at $t = 1$ and request a payment of 1.5 Taler. The bank then has to divest a part of the long-term project to generate enough liquidity to pay out the two depositors. Out of the initial 6 Taler that were invested in the project only 3 Taler remain invested. The balance sheet of the bank thus shrank to a new value of 3 Taler. On these 3 Taler that remain invested a return R is generated.

At time $t = 2$, the project is liquidated and makes the balance sheet of the bank grow. All the money that is in the balance sheet of the bank will then be distributed equally among the remaining depositors. We immediately see that the return of any given investor does not only depend on the return of the project but also on how many depositors withdraw their money in $t = 1$.

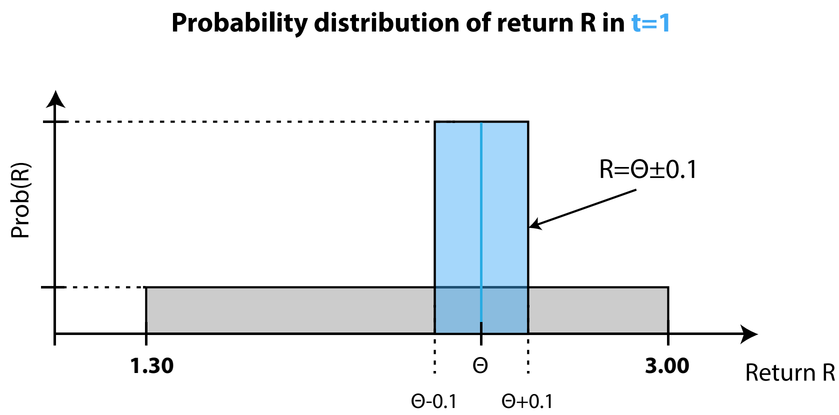
What happens if at time $t = 1$ many depositors decide to withdraw early? Let us look at a situation in which five depositors decide to withdraw early. The depositors collectively ask for an early payment of 5 times 1.5 Taler at time $t = 1$ from the bank. The bank, however, can only liquidate 6 Taler from the project. Thus, the bank has to close down the project and declares bankruptcy. The bank distributes the proceeds of 6 Taler among four of the five early withdrawers. A random mechanism chooses four out of the five depositors that receive the 1.5 Taler. It is thus possible that an investor decides to withdraw early but nevertheless does not receive any payment since the bank is bankrupt. One early withdrawer and one late withdrawer get nothing.

Let us summarize the process: At time $t = 0$ six depositors invest 1 Taler each in a bank. The bank collects 6 Taler and invests them in a long-term project. At time $t = 1$ the depositors receive a private noisy signal θ about the value of R and then decide whether they want to withdraw early. The bank has to liquidate part of the investment if there are depositors that withdraw early. If four or more depositors decide to withdraw early the bank goes bankrupt. Any remaining investment yields a return R at time $t = 2$ and is equally distributed among the remaining depositors.

The following illustration shows how to interpret the signal. At time $t = 0$ we do not know the return R. We only know that it lies in the interval of 1.3 and 3.0. At time $t = 1$ every depositor receives a private signal θ that limits the range of the true return to $R = \theta \pm 0.1$.[1] The values in that range are uniformly distributed.

To help you decide quickly you will see a payout table as follows. In the first two columns you see a possible combination of early and late withdrawers. Depending on the number of early and late withdrawers a different result realizes in time $t = 1$ and $t = 2$. As an example we assume that the project yields a return of $R = 3$. In every row we see a possible combination of early and late withdrawers. If we assume that no one withdraws money early then we are in the first row. We thus face zero early withdrawers and six late

[1] The "Noisy Bank Run Treatment" equals the regular bank run treatment with the only exception that the value for the noise term ϵ equals 0.3 instead of 0.1, i.e., the range of R is $[\theta - 0.3, \theta + 0.3]$.



withdrawers. At time $t = 1$ no one has to paid out and the project is liquidated in period $t = 2$. Since the project offers a return of $R = 3$, every depositor receives a payment of 3 Taler. Of the six late withdrawers all six are happy with their decision since they got their money back.

		Period 1			Period 2		
Number of early withdrawers (withdraw in t=1)	Number of late withdrawers (withdraw in t=2)	Number of satisfied early withdrawers	Number of unsatisfied early withdrawers	Individual Payoff	Number of satisfied late withdrawers	Number of unsatisfied late withdrawers	Individual Payoff
0	6	-	-	-	6	0	**3.00**
1	5	1	0	**1.50**	5	0	**2.70**
2	4	2	0	**1.50**	4	0	**2.25**
3	3	3	0	**1.50**	3	0	**1.50**
4	2	4	0	**1.50**	0	2	**0.00**
5	1	4	1	**0.00 or 1.50**	0	1	**0.00**
6	0	4	2	**0.00 or 1.50**	-	-	-

If we assume that two depositors withdraw their money early we are in the third row. We thus have two early withdrawers and four late withdrawers. The bank has enough funds to pay out the two early withdrawers in $t = 1$. Both receive their payment of 1.5 and are happy that they got their requested money. In time $t = 2$ the four remaining depositors get the proceeds of what remained invested in the project. In this case they get 2.25 Taler per depositor. How do we get to these 2.25? The payoff of 2.25 is the result of the remaining investment, i.e., 6 Taler minus the payment for the early withdrawers, is multiplied with the return of the project R. This amount is divided by the number of late withdrawers. In this example, two depositors withdraw their deposits early, i.e., 3 Taler remain invested and yield a return of 3. We thus have an amount of 9 Taler that is distributed among the four remaining depositors.
Since all late withdrawers can be paid out, all of them are happy.
Now the experiment starts. Remember that you have to focus on your task and collect as many Taler as possible in order to get as many pralines as possible. Have fun investing and withdrawing money. Thank you.

A.1.4 Guess the Number Treatment

Guess the Number (1/5): Introduction

Information

- In this part of the experiment you try to guess the right number.
- Depending on how good you are at guessing you will receive a bonus paid out in Taler.
- **Important:** All answers are treated completely confidentially and are only analyzed in an anonymous form.

Guess the Number (2/5): First guess

Rules of the game

- All participants of the experiment guess a number in the interval of **0** to **100**.
- The person that comes closest to **2/3 of the average of all estimates** wins a bonus of **50 Taler**.
- If there is more than one winner, the 50 Taler will be split among the winners.
- **Example:** 5 persons play the game and estimate 10, 20, 30, 40, and 50. The average is 30, 2/3 of 30 is 20. Thus, the person that was guessing 20 wins the game.

Guess

Your guess for **2/3 of the average of all estimates:**

`short text field`

(*Format:* XXX.YY with a point for decimal notation)

Guess the Number (3/5): First explanation

Your guess

Your guess of 2/3 of the average was: [guess$_{i,2}$]

Explanation

Please describe in a few words your thoughts how you came to your decision.

`long text field`

Guess the Number (4/5): Second guess

****Additional information****
In an earlier round the average of all estimates was at 36.73. The guess 24.49 (=2/3 of 36.73) was the winning number then.
Rules of the game

- All participants of the experiment guess a number in the interval of **0** to **100**.
- The person that comes closest to **2/3 of the average of all estimates** wins a bonus of **50 Taler**.
- If there is more than one winner, the 50 Taler will be split among the winners.
- **Example:** 5 persons play the game and estimate 10, 20, 30, 40, and 50. The average is 30, 2/3 of 30 is 20. Thus, the person that was guessing 20 wins the game.

Guess

Your guess for **2/3 of the average of all estimates:**

`short text field`

Guess the Number (5/5): Second explanation

Your guess

Your guess of 2/3 of the average was: [guess$_{i,2}$]

Explanation

Please describe in a few words your thoughts how you came to your decision.

`long text field`

A.1.5 Questionnaire

Final questionnaire (1/4): Decision Taking

This is the end of the main part of the experiment. Now some questions about the game and your chosen strategy will follow.

Your last decision in the bank run game

Your private signal θ for the decision to withdraw early or late was: $\theta = [\theta_{i,20}]$

Your decision for this signal was: [withdraw early, withdraw late]

The true return for this decision situation was: $R = [R_{i,20}]$

Your payoff from this decision situation was: $\text{Payoff}_{i,20}$ Taler

Please describe in a few words your thoughts how you came to your decision.

`long text field`

Final questionnaire (2/4): Lottery Choice

Please decide between the two lotteries in the next ten cases. The payoffs remain the same but the corresponding probabilities change from row to row.

Reading example: in the first row you decide between lottery A and B. Lottery A offers a payoff of \$2.00 in 10% of all cases, and \$1.60 in 90% of all cases, while lottery B offers \$3.85 in 10% of all cases, and \$0.10 in 90% of all cases.

Please indicate your relative preference for every row.[2]

Lottery A			**Lottery B**
with 10% \$2.00 / with 90% \$1.60	○	○	with 10% \$3.85 / with 90% \$0.10
with 20% \$2.00 / with 80% \$1.60	○	○	with 20% \$3.85 / with 80% \$0.10
with 30% \$2.00 / with 70% \$1.60	○	○	with 30% \$3.85 / with 70% \$0.10
with 40% \$2.00 / with 60% \$1.60	○	○	with 40% \$3.85 / with 60% \$0.10
with 50% \$2.00 / with 50% \$1.60	○	○	with 50% \$3.85 / with 50% \$0.10
with 60% \$2.00 / with 40% \$1.60	○	○	with 60% \$3.85 / with 40% \$0.10
with 70% \$2.00 / with 30% \$1.60	○	○	with 70% \$3.85 / with 30% \$0.10
with 80% \$2.00 / with 20% \$1.60	○	○	with 80% \$3.85 / with 20% \$0.10
with 90% \$2.00 / with 10% \$1.60	○	○	with 90% \$3.85 / with 10% \$0.10
with 100% \$2.00 / with 0% \$1.60	○	○	with 100% \$3.85 / with 0% \$0.10

[2] The program tested for consistency of the replies: subjects were prohibited to change preferences more than once. Furthermore, the program produced a pop up error message ("Please check your choice in the last row. Are you sure you prefer a secure payment of \$2.00 over a secure payment of \$3.85?") if the last decision was not lottery B.

Final questionnaire (3/4): Experiment Details

How much do you like chocolate?

	1	2	3	4	5	6	
not at all	◯	◯	◯	◯	◯	◯	very much

How much do you like Lindt & Sprüngli Lindor pralines?

	1	2	3	4	5	6	
not at all	◯	◯	◯	◯	◯	◯	very much

How much did you enjoy participating in the experiment?

	1	2	3	4	5	6	
not at all	◯	◯	◯	◯	◯	◯	very much

Would you like to participate again in classroom experiments?

	1	2	3	4	5	6	
not at all	◯	◯	◯	◯	◯	◯	very much

How well did you understand the instructions of the experiment?

	1	2	3	4	5	6	
very badly	◯	◯	◯	◯	◯	◯	very well

Did you already know the "Bank Run Game" from an earlier experiment?

◯ yes
◯ no

Did you already know the "Guess the Number Game" from an earlier experiment?

◯ yes
◯ no

Have you participated / watched the lecture on "Bank Runs"?

◯ yes, as an online podcast
◯ yes, as a live lecture in the lecture hall
◯ no

Final questionnaire (4/4): Demographics

Gender

- ◯ female
- ◯ male

Age

`short text field`

Semester

1	2	3	4	5	6	7	8	>8
◯	◯	◯	◯	◯	◯	◯	◯	◯

Field of study

- ◯ Banking & Finance
- ◯ Business Administration
- ◯ Management & Economics
- ◯ Economics
- ◯ Informatics
- ◯ Other major (minor subject student)

Other remarks / comments / feedback

`long text field`

A.2 Supplementary Tables

Supplementary Table A-1

OLS Regression Models for the Estimated Logit Thresholds. This table presents OLS regression results for the estimated individual logit thresholds. The dependent variable is the most likely threshold estimated in the logit regression model based on signals alone. Explanatory variables are identical to the models (1) to (11) from Table 1.7 except for the time varying variables signal and period. All models include control variables for the session (not reported). t-statistics using robust standard errors are reported in parentheses. *** indicate statistical significance at $p < 0.01$, ** at $p < 0.05$, and * at $p < 0.1$.

		Estimations											*Mg. eff.*
Logit Threshold	HYP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	*(11)*
I(Boom)	(−)		-0.007									-0.027	*-0.027*
			(-0.32)									(-0.36)	
I(Bust)	(+)		0.044*	0.053**								0.000	*0.000*
			(1.89)	(2.23)								(0.00)	
I(GTN First)	(+)				0.035**	0.035**	0.032*					0.035**	*0.035*
					(2.05)	(2.02)	(1.79)					(1.97)	
Level-k Estimate	(+)					0.004	0.015**					0.013**	*0.025*
						(1.28)	(2.58)					(2.13)	
I(Noisy Signals)	(+)							0.072***				0.060**	*0.060*
								(2.65)				(2.30)	
Risk aversion	(+)								-0.007			-0.000	*0.000*
									(-1.25)			(-0.01)	
Affective State	(−)									0.002		0.003	*0.018*
										(0.82)		(0.30)	
Fearfulness	(+)									0.002		0.009	*0.018*
										(0.29)		(0.77)	
I(Female)	(+/−)										-0.040**	-0.049**	*-0.049*
											(-2.05)	(-2.45)	
Constant		1.855***	1.843***	1.831***	1.836***	1.817***	1.787***	1.848***	1.885***	1.841***	1.867***	1.795***	
		(115.09)	(93.19)	(75.18)	(101.96)	(77.56)	(63.43)	(74.33)	(61.27)	(92.56)	(112.42)	(43.93)	
Observations		555	466	312	555	555	511	243	553	466	550	504	
Treatment Filter		None	No Pr.	Noisy	None	L-∞	None	L-∞	Noisy	Priming	None	L-∞	
R-squared		0.007	0.017	0.017	0.014	0.018	0.033	0.053	0.010	0.008	0.013	0.052	

B Appendix: Chapter 2

B.1 Scene of Gnomes in "Faust"

Gnomes.
The little crowd comes tripping there
They don't associate pair by pair.
In mossy garb, with lantern bright.
They move commingling, brisk and light,
Each working on his separate ground,
Like fire fly insects swarming round;
And press and gather here and there,
Always industrious everywhere.
With the "Good People" kin we own;
As surgeons of the rocks we're known.
Cupping the mountains, bleeding them
From fullest veins, depleting them
Of store of metals, which we pile,
And merrily greet: "Good cheer!" the while.
Well-meant the words, believe us, then!
We are the friends of all good men.
Yet we the stores of gold unseal
That men may pander, pimp, and steal ;
Nor iron shall fail his haughty hand
Who universal murder planned:
And who these three Commandments breaks
But little heed o' the others takes.
For that we're not responsible:
We're patient – be you, too, as well.

Gnomen.
Da trippelt ein die kleine Schar,
Sie hält nicht gern sich Paar und Paar;
Im moosigen Kleid mit Lämplein hell
Bewegt sich's durcheinander schnell,
Wo jedes für sich selber schafft,
Wie Leucht-Ameisen wimmelhaft;
Und wuselt emsig hin und her,
Beschäftigt in die Kreuz und Quer.
Den frommen Gütchen nah verwandt,
Als Felschirurgen wohlbekannt;
Die hohen Berge schröpfen wir,
Aus vollen Adern schöpfen wir;
Metalle stürzen wir zuhauf,
Mit Gruß getrost: Glück auf! Glück auf!
Das ist von Grund aus wohlgemeint:
Wir sind der guten Menschen Freund.
Doch bringen wir das Gold zu Tag,
Damit man stehlen und kuppeln mag,
Nicht Eisen fehle dem stolzen Mann,
Der allgemeinen Mord ersann.
Und wer die drei Gebot' veracht't,
Sich auch nichts aus den andern macht.
Das alles ist nicht unsre Schuld;
Drum habt so fort, wie wir, Geduld.

Johann Wolfgang von Goethe: Faust – a Tragedy
Translated by Bayard Taylor; Ward, Lock and Co., London and N.Y., 1889; Ch. 11.

B.2 Supplementary Tables

Supplementary Table B-1

Media Dummy Generation and Search Terms. For each institution in the database we conduct a media search in LexisNews Academic International News and Wire database. In a first step all articles are collected from two large national Swiss newspapers and the largest Swiss news agency that fulfill certain search criteria. In this step each institution's name is connected with the following search terms. In order to account for different spellings or plural/singular occurrences of distinct word, we use the following search operators. "!" picks up any number of letters after a root word; "$*$" serves as a placeholder for one letter; "w/n" is a proximity connector which is used to establish a relationship between terms; the letter "n" can present an arbitrary number. This results in a list of 4,380 articles for 98 banks in the period 2002-2014. From this list we generate for every bank and every year a dummy variable whether the bank has been covered in the newspaper in relation with any of the search terms. The dummy variable *Overall Media Coverage* takes on a value of 1 if there has been at least one newspaper article about the institution in the given year. In a second step we analyze all these manually whether the media coverage has had a negative sentiment. To rule out personal biases we conduct this second step twice by two different individuals. The dummy variable *Negative Media Coverage* takes on a value of 1 if there has been at least one negative newspaper article about the institution in the given year.

Search Terms	
Amnestie w/10 steuer	Kunden!
nicht w/2 deklariert*	Repatr!
Amtshilf!	Schwarzgeld
angeklag!	Scudo!
anklage	Steuerab!
Bankd!	Steuerbe!
Bankgeheim!	Steuerdaten
Doppelbest!	Steuerfl!
Finanza!	Steuerhinter!
Finanzp!	Steuersünd!
Geldw!	Steuerver!
Gesetz!	Strafsteuer
IRS!	unversteuert*
Kont**dat!	

Supplementary Table B-2

Correlation Matrix CIR-Estimation. This table shows a correlation matrix for the regressors used in the CIR estimation. For definitions of the variables see Table 2.2. * indicates statistical significance at $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
(1) Cost-Income Ratio (incl. dep.)	1				
(2) Personnel Costs / Tot. Costs	-0.30*	1			
(3) Depreciation Costs / Tot. Costs	0.11	-0.19	1		
(4) Fee & Com. Income / Op. Rev.	0.16	0.17	-0.28*	1	
(5) Trading Income / Op. Rev.	0.02	-0.19	-0.05	-0.34*	1
(6) Log(Assets under Management)	-0.23*	0.21*	0.14	-0.15	-0.19

Supplementary Table B-3

Correlation Matrix NNM-Estimation. This table shows a correlation matrix for the regressors used in the NNM estimation. For definitions of the variables see Table 2.3. * indicates statistical significance at $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Net New Money / AvAuM	1												
(2) Abnormal CIR (ζ_i)	-0.15	1											
(3) Abnormal CIR Year (ϵ_{it})	0.06	0.02	1										
(4) Negative Media Coverage	-0.09	0.34*	0.09	1									
(5) NegMedCov X AuM>Med	-0.09	0.44*	0.03	0.89*	1								
(6) AuM Above Median	-0.12	0.79*	0.06	0.33*	0.49*	1							
(7) Equity Ratio	-0.06	-0.55*	0.07	-0.33*	-0.32*	-0.52*	1						
(8) Service Quality	-0.08	-0.16	0.04	-0.03	-0.08	-0.35*	0.18	1					
(9) Wage Costs per Employee	0.09	0.36*	0.09	-0.13	-0.06	0.35*	-0.12	-0.53*	1				
(10) Growth of Number of Emp.	0.59*	0.04	0.18	-0.14	-0.03	0.07	-0.05	-0.16	0.35*	1			
(11) Client Value	-0.15	0.13	-0.19	-0.06	0.13	0.15	0.04	-0.23*	0.32*	0.31*	1		
(12) Own Funds / AvAuM	-0.02	0.05	0.15	0.06	0.08	0.00	0.18	0.02	-0.12	-0.15	0.11	1	
(13) Mgmt Mandates / AvAuM	-0.00	-0.30*	0.01	-0.17	-0.18	-0.14	0.47*	-0.09	-0.03	0.05	0.15	0.11	1
(14) Bank Domiciled in FL	0.24*	-0.35*	0.01	-0.12	-0.14	-0.27*	-0.14	-0.17	-0.17	0.11	-0.15	-0.17	-0.11

Supplementary Table B-4

Robustness Check – Rich CIR Model Residuals. This table presents random effects panel regression results for six different models to estimate the performance of a private bank as measured by net new money flows. The dependent variable is the Net New Money scaled by AvAuM. All explanatory variables are lagged by one year. The bank-specific abnormal cost-income ratio (ζ_i) as well as the bank-year-specific cost-income ratio (ϵ_{it}) are predicted from the richest model specification (6) in Table 2.4. All other regressors definitions are identical to the descriptive statics Tables 2.2 and 2.3. Z-statistics based on robust standard errors clustered on banks are reported in parentheses. *** indicate statistical significance at $p < 0.01$, ** at $p < 0.05$, and * at $p < 0.1$.

		Models					
Net New Money / AvAuM	Hyp	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal CIR (ζ_i)	(−)	-0.075***	-0.091***	-0.093***	-0.114***	-0.073**	-0.084**
		(-2.70)	(-2.98)	(-3.13)	(-3.49)	(-2.57)	(-2.43)
Abnormal CIR Year (ϵ_{it})	(?)	-0.116***	-0.114***	-0.136***	-0.119***	-0.097**	-0.110**
		(-2.75)	(-2.72)	(-3.28)	(-2.72)	(-2.05)	(-2.37)
Negative Media Coverage	(−)	-0.095***	-0.101***	-0.094***	-0.108***	-0.099***	-0.106***
		(-3.63)	(-3.70)	(-3.42)	(-3.49)	(-3.54)	(-3.70)
NegMedCov X [AuM > Med]	(+)	0.059**	0.067**	0.059**	0.075**	0.061**	0.075**
		(2.10)	(2.31)	(1.98)	(2.33)	(2.01)	(2.48)
AuM Above Median	(+)	0.036**	0.033*	0.053***	0.048***	0.040**	0.042**
		(2.10)	(1.94)	(3.11)	(2.85)	(2.39)	(2.51)
Equity Ratio	(?)		-0.124*		-0.208***		-0.214***
			(-1.81)		(-2.95)		(-3.03)
Service Quality	(+)			2.324***	1.833**		2.268***
				(2.74)	(2.22)		(2.72)
Wage Costs per Employee	(+)			0.195	0.204		0.281*
				(1.31)	(1.30)		(1.78)
Growth of Number of Emp.	(+)				0.040		0.024
					(1.16)		(0.71)
Client Value	(+)					0.028	0.014
						(0.64)	(0.32)
Own Funds / AvAuM	(+)						0.142**
							(2.12)
Mgmt Mandates / AvAuM	(−)						0.051
							(1.31)
Bank domiciled in FL	(?)						0.071***
							(3.16)
Constant		0.064***	0.092***	-0.036	-0.010	0.033***	-0.054
		(3.56)	(3.80)	(-0.79)	(-0.22)	(2.66)	(-1.19)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Observations		607	607	607	551	536	536
Number of Banks		96	96	96	92	92	92
R2_within		0.13	0.13	0.17	0.17	0.13	0.17
R2_between		0.02	0.06	0.02	0.07	0.02	0.13
R2_overall		0.09	0.10	0.10	0.14	0.10	0.16

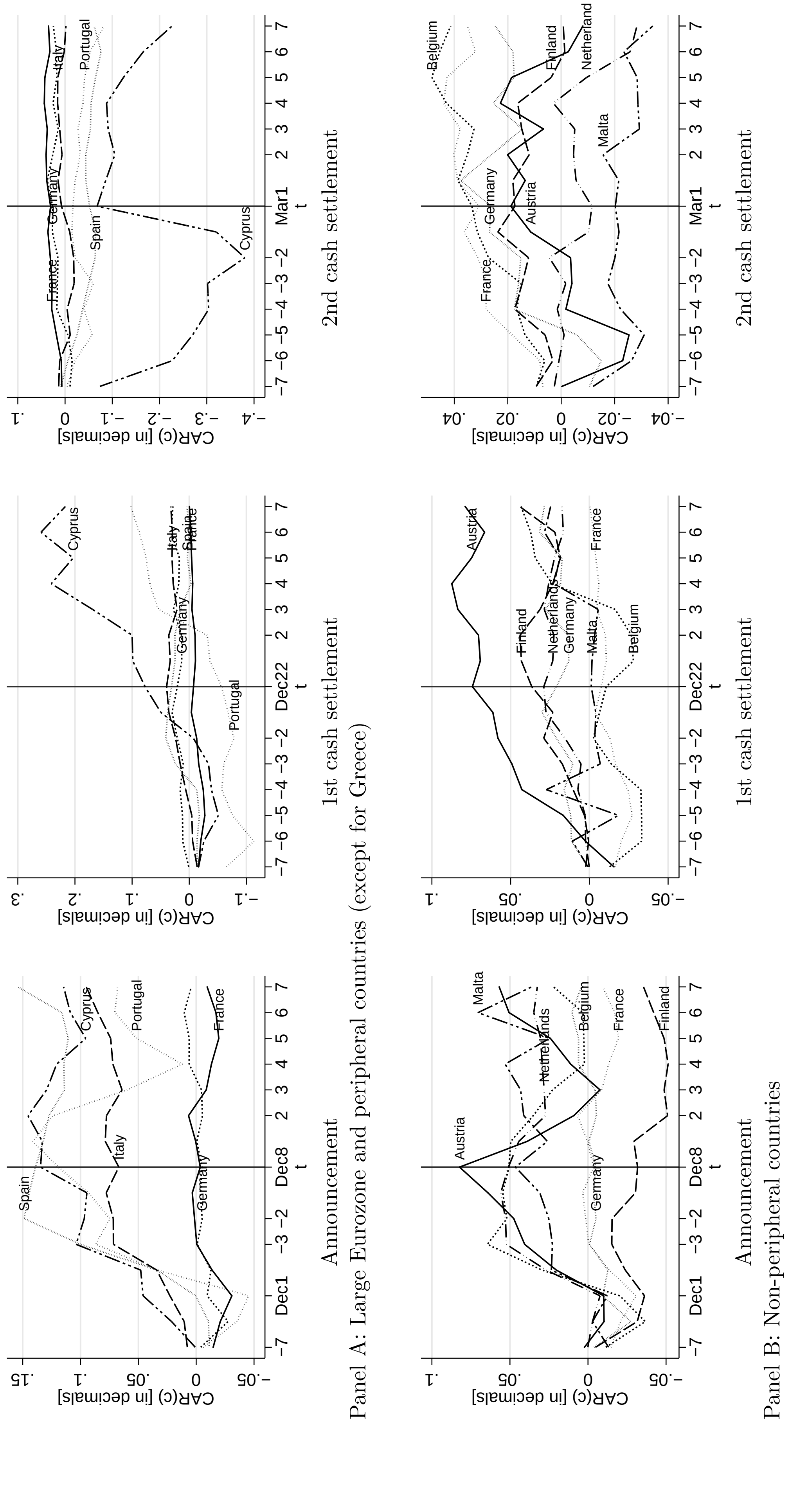
Supplementary Table B-5

Robustness Check – NNM Fixed Effects Estimation. This table presents *fixed effects* panel regression results for six different models to estimate the performance of a private bank as measured by net new money flows. The dependent variable is the Net New Money scaled by AvAuM. All explanatory variables are lagged by one year. The bank-specific abnormal cost-income ratio (ζ_i) as well as the bank-year-specific cost-income ratio (ϵ_{it}) are predicted from the richest model specification (6) in Table 2.4. All other regressors definitions are identical to the descriptive statics Tables 2.2 and 2.3. Z-statistics based on robust standard errors clustered on banks are reported in parentheses. *** indicate statistical significance at $p < 0.01$, ** at $p < 0.05$, and * at $p < 0.1$.

		Models					
Net New Money / AvAuM	Hyp	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal CIR Year (ϵ_{it})	(?)	-0.120***	-0.120***	-0.156***	-0.135***	-0.093*	-0.117**
		(-2.77)	(-2.78)	(-3.42)	(-2.79)	(-1.90)	(-2.33)
Negative Media Coverage	(−)	-0.082**	-0.083**	-0.083***	-0.091***	-0.082**	-0.089***
		(-2.52)	(-2.49)	(-2.71)	(-2.98)	(-2.61)	(-2.88)
NegMedCov X [AuM > Med]	(−)	0.050	0.051	0.047	0.057*	0.046	0.052
		(1.41)	(1.42)	(1.43)	(1.78)	(1.34)	(1.57)
AuM Above Median	(+)	0.068**	0.069**	0.079***	0.081***	0.065**	0.073***
		(2.54)	(2.53)	(3.26)	(3.16)	(2.27)	(2.86)
Equity Ratio	(?)		-0.037		-0.227**		-0.231**
			(-0.35)		(-2.12)		(-2.14)
Service Quality	(+)			4.411***	4.834***		5.340***
				(3.72)	(3.18)		(3.29)
Wage Costs per Employee	(+)			0.277	0.355		0.295
				(1.14)	(1.38)		(1.16)
Growth of Number of Emp.	(+)				-0.024		-0.059
					(-0.65)		(-1.58)
Client Value	(+)					0.034	0.062
						(0.77)	(1.29)
Own Funds / AvAuM	(+)						0.108
							(0.75)
Mgmt Mandates / AvAuM	(−)						0.132
							(1.46)
Constant		0.052***	0.060**	-0.112*	-0.116*	0.043**	-0.134**
		(2.98)	(2.14)	(-1.78)	(-1.74)	(2.30)	(-2.00)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Observations		607	607	607	551	536	536
Number of Banks		96	96	96	92	92	92
R2_within		0.13	0.14	0.18	0.19	0.14	0.20
R2_between		0.02	0.02	0.01	0.00	0.00	0.00
R2_overall		0.03	0.03	0.04	0.04	0.04	0.05

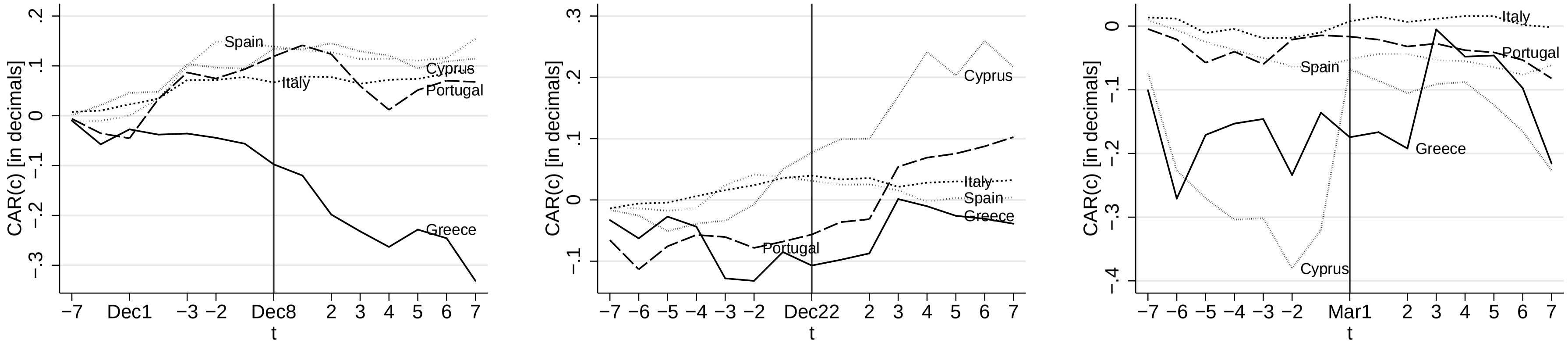
C Appendix: Chapter 3

C.1 Supplementary Figures and Tables



Panel A: Large Eurozone and peripheral countries (except for Greece)

Panel B: Non-peripheral countries



Announcement

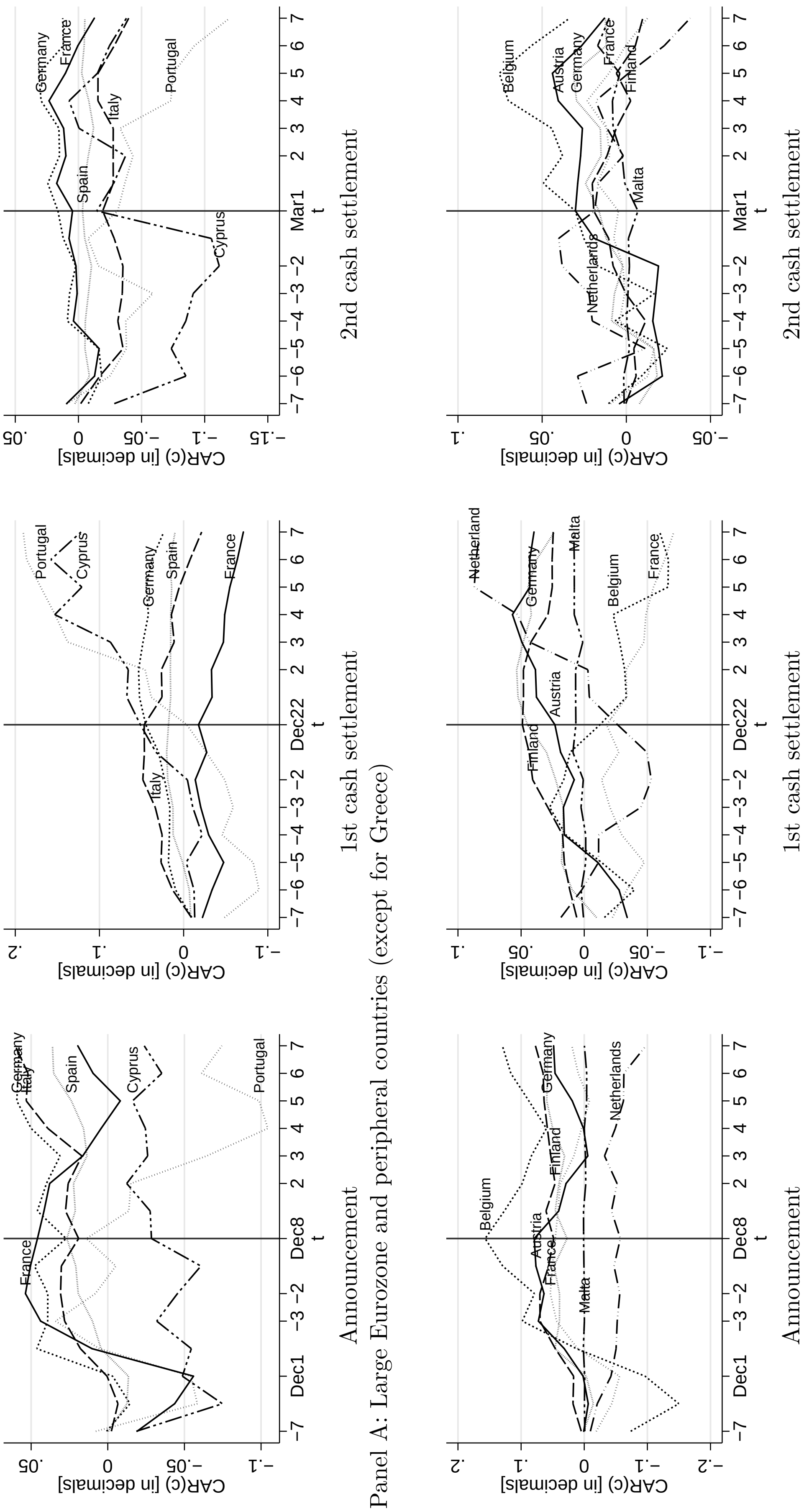
1st cash settlement

2nd cash settlement

Panel C: Peripheral countries

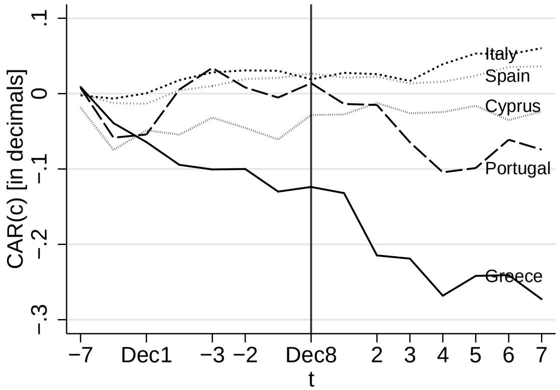
Supplementary Figure C-1

Average cumulative abnormal returns on bank stocks by country using the STOXX Europe 600 index. This figure is based on the bank stock sample and provides country-level averages of cumulative abnormal returns, CAR_c, across banks, CAR_i, for the three different events separately. CAR_i is the sum over abnormal returns for bank i, $AR_{i,t}$, over the event window $[-7, 7]$. $AR_{i,t}$ is estimated from the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event separately. $r_{m,t}$ is, for each country, based on the STOXX Europe 600 index. The three columns of subplots represent the three events indicated by vertical lines in each subplot: announcement, 1st cash settlement, and 2nd cash settlement of the three-year LTROs on December 8, 2011, December 22, 2011, and March 1, 2012, respectively. The vertical line at December 1, 2011 in the first column of subplots represents the ECB's first indication of large-scale help for banks. Panel A covers large Eurozone countries (Germany and France) as well as peripheral countries (except for Greece). Panels B and C cover non-peripheral and peripheral countries, respectively.

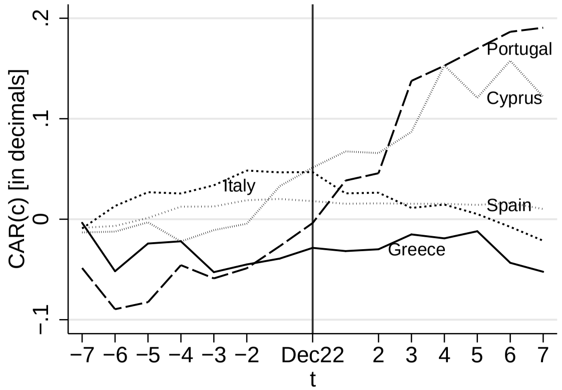


Panel A: Large Eurozone and peripheral countries (except for Greece)

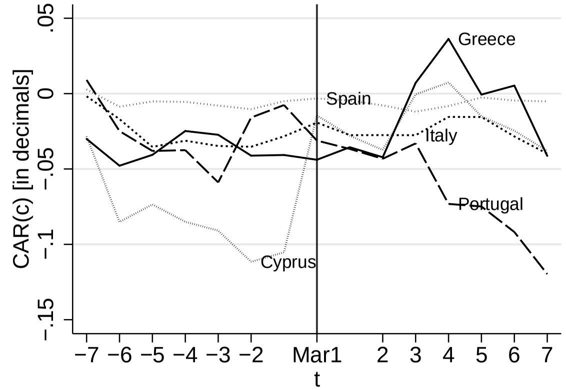
Panel B: Non-peripheral countries



Announcement



1st cash settlement



2nd cash settlement

Panel C: Peripheral countries

Supplementary Figure C-2

Average Cumulative Abnormal Returns on Bank Indices by Country Using Country-Level Market Index. This figure is based on the bank index sample and provides cumulative abnormal returns, CAR_c for the three different events separately. CAR_c is the sum over abnormal returns in country c, $AR_{c,t}$, over the event window $[-7, 7]$. $AR_{c,t}$ is estimated from the market model in Eq. 3.2 but using subscript c instead of i and using the estimation window $[T_0, T_1] = [-192, -8]$ for each event separately. $r_{m,c}$ is based on a country-level total market return index (for details see Section 3.3). The three columns of subplots represent the three events indicated by vertical lines in each subplot: announcement, 1st cash settlement, and 2nd cash settlement of the three-year LTROs on December 8, 2011, December 22, 2011, and March 1, 2012, respectively. The vertical line at December 1, 2011 in the first column of subplots represents the ECB's first indication of large-scale help for banks. Panel A covers large Eurozone countries (Germany and France) as well as peripheral countries (except for Greece). Panels B and C cover non-peripheral and peripheral countries, respectively.

Supplementary Table C-1

Comparison of Abnormal Returns on Equally-Weighted Portfolios of Bank Stocks on Event versus Non-Event Days per Country. This table compares estimated abnormal returns on event to those on non-event days for the equally-weighted bank stock portfolio sample by country. Numbers are in percentage points. Countries are classified into non-peripheral and peripheral countries as indicated in the table. Each of the three panels provides sample means, medians, standard deviations, and number of observations on event days and non-event days. In each panel and for each country the table shows two-sample t-tests for equal means, Kruskal-Wallis χ^2-tests for equal medians, and variance-ratio F-tests for equal variances comparing event and non-event day abnormal returns. Abnormal returns are estimated with the market model in Eq. 3.2 (by replacing subscript i by subscript c) using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is based on a country-level total market return index (see Section 3.3). For each country in each panel the tests are based on a total of $[-192, 7] = 200$ days: $[-7, 7] = 15$ event days and $[-192, -8] = 185$ non-event days. In Panel A, $t = 0$ is the announcement of the three-year LTROs on December 8, 2011. In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). Test statistics and corresponding means, medians, and/or variances that are significant at the level of at least 10% are marked in bold. a, b, and c next to the test statistics denote significance at the levels of 1%, 5%, and 10%, respectively.

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel A: December 8, 2011 (announcement of three-year LTROs)													
Event	Mean	0.332	0.234	0.248	0.060	0.183	0.435	0.041	**-2.717**	**0.638**	0.425	**1.021**	0.768
days	Med	**0.675**	-0.463	0.562	0.127	0.242	0.344	-0.072	**-2.200**	**0.700**	-0.007	**0.101**	0.196
	SD	1.268	1.824	1.059	0.831	0.925	2.206	1.116	4.054	0.668	3.440	2.039	2.277
	Obs	15	15	15	15	15	15	15	15	15	15	15	15
Non-	Mean	0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000	**0.000**	**0.000**	-0.000	**-0.000**	0.000
event	Med	**-0.001**	0.068	-0.034	0.037	-0.002	-0.036	0.053	**-0.209**	**-0.012**	0.054	**-0.039**	0.128
days	SD	0.917	0.972	0.897	0.606	1.064	2.490	0.766	4.826	0.625	1.830	0.787	2.532
	Obs	185	185	185	185	185	185	185	185	185	185	185	185
Event vs non-event days:	*Test for equal*												
means	TT t-stat	-0.992	-0.491	-0.881	-0.275	-0.729	-0.727	-0.140	**2.458**^{b}	**-3.571**^{a}	-0.473	**-1.928**^{c}	-1.245
	TT p-val	0.337	0.631	0.392	0.787	0.476	0.477	0.891	0.025	0.003	0.643	0.074	0.230
meds	KW χ^2-stat	**3.066**^{c}	0.154	1.891	0.069	1.255	0.926	0.500	**6.123**^{b}	**11.829**^{a}	0.361	**2.890**^{c}	0.814
	KW p-val	0.080	0.695	0.169	0.793	0.263	0.336	0.479	0.013	0.001	0.548	0.089	0.367
vars	VR F-stat	**0.523**^{c}	**0.284**^{a}	0.718	**0.531**^{c}	1.324	1.273	**0.471**^{b}	1.417	0.875	**0.283**^{a}	**0.149**^{a}	1.236
	VR p-val	0.055	0.000	0.319	0.061	0.568	0.632	0.025	0.466	0.647	0.000	0.000	0.683

Table to be continued

Table C-1 – continued

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel B: December 22, 2011 (first three-year LTRO cash settlement)													
Event days	Mean	0.155	0.280	0.201	0.036	0.267	0.421	-0.053	-0.962	0.253	0.429	0.074	0.647
	Med	0.156	0.139	0.347	0.042	0.277	0.369	-0.112	-1.367	0.332	0.616	-0.231	0.071
	SD	0.760	1.364	0.756	0.502	0.762	1.895	0.419	3.892	0.611	3.021	1.027	3.396
	Obs	15	15	15	15	15	15	15	15	15	15	15	15
Non-event days	Mean	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
	Med	0.016	0.038	-0.022	0.032	0.024	-0.066	0.051	-0.090	-0.028	-0.003	-0.094	0.078
	SD	0.893	1.064	0.924	0.629	1.049	2.482	0.797	4.903	0.658	1.965	0.972	2.564
	Obs	185	185	185	185	185	185	185	185	185	185	185	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.747	-0.777	-0.974	-0.262	-1.262	-0.806	0.429	0.901	-1.533	-0.541	-0.268	-0.721
	TT p-val	0.465	0.449	0.344	0.796	0.223	0.431	0.672	0.379	0.144	0.597	0.792	0.482
meds	KW χ^2-stat	0.865	0.568	1.318	0.047	1.265	2.061	0.180	1.361	2.393	1.517	0.267	0.277
	KW p-val	0.352	0.451	0.251	0.829	0.261	0.151	0.671	0.243	0.122	0.218	0.605	0.599
vars	VR F-stat	1.383	0.609	1.491	1.569	1.895	1.716	**3.614**^{a}	1.587	1.161	**0.423**^{a}	0.895	**0.570**^{c}
	VR p-val	0.501	0.143	0.398	0.337	0.170	0.247	0.009	0.324	0.796	0.010	0.690	0.097
Panel C: March 1, 2012 (second three-year LTRO cash settlement)													
Event days	Mean	0.096	0.206	0.056	0.122	0.133	-0.240	-0.122	-0.240	-0.066	**-0.734**	0.009	-0.530
	Med	0.193	0.127	0.101	0.155	-0.056	-0.007	-0.049	-0.552	0.098	-0.448	-0.432	-1.757
	SD	0.979	0.520	0.605	0.550	1.103	1.080	0.693	5.100	0.654	1.438	1.163	7.716
	Obs	15	15	15	15	15	15	15	15	15	15	15	15
Non-event days	Mean	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	**-0.000**	0.000	-0.000
	Med	0.000	-0.016	-0.060	0.000	-0.020	-0.118	-0.020	-0.229	-0.084	-0.082	-0.084	0.001
	SD	0.952	1.218	0.972	0.701	1.112	1.595	0.865	5.322	0.772	2.418	1.016	3.154
	Obs	185	185	185	185	185	185	185	185	185	185	185	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.368	-1.279	-0.325	-0.810	-0.451	0.793	0.643	0.175	0.372	**1.783**^{c}	-0.030	0.264
	TT p-val	0.718	0.211	0.749	0.429	0.658	0.437	0.529	0.864	0.715	0.089	0.976	0.795
meds	KW χ^2-stat	0.395	1.244	0.200	0.773	0.047	0.030	0.143	0.575	0.000	2.524	0.035	2.480
	KW p-val	0.530	0.265	0.654	0.379	0.829	0.862	0.705	0.448	0.990	0.112	0.851	0.115
vars	VR F-stat	0.946	**5.482**^{a}	**2.581**^{b}	1.627	1.017	**2.182**^{c}	1.559	1.089	1.392	**2.828**^{b}	0.763	**0.167**^{a}
	VR p-val	0.800	0.001	0.046	0.298	0.945	0.096	0.344	0.919	0.491	0.030	0.409	0.000

Supplementary Table C-2

Comparison of Abnormal Returns on Bank Stocks on Event versus Non-Event Days Using “STOXX Europe 600” as the Market Index. This table compares estimated abnormal returns on event to those on non-event days for the bank stock sample by country. Numbers are in percentage points. Countries are classified into non-peripheral and peripheral countries as indicated in the table. Each of the three panels provides sample means, medians, standard deviations, and number of observations on event days and non-event days. In each panel and for each country the table shows two-sample t-tests for equal means, Kruskal-Wallis χ^2-tests for equal medians, and variance-ratio F-tests for equal variances comparing event and non-event day abnormal returns. Abnormal returns are estimated with the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is, for each country, based on the STOXX Europe 600 index. For each country in each panel the tests are based on a total of $[-192, 7] = 200$ days: $[-7, 7] = 15$ event days and $[-192, -8] = 185$ non-event days. In Panel A, $t = 0$ is the announcement of the three-year LTROs on December 8, 2011. In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). Test statistics and corresponding means, medians, and/or variances that are significant at the level of at least 10% are marked in bold. a, b, and c next to the test statistics denote significance at the levels of 1%, 5%, and 10%, respectively.

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel A: December 8, 2011 (announcement of three-year LTROs)													
Event days	Mean	0.379	0.147	-0.237	-0.063	0.028	0.241	0.217	**-2.208**	**0.634**	0.453	**1.028**	0.764
	Med	0.454	-0.167	-0.012	0.014	-0.201	0.234	0.040	**-1.737**	**0.323**	-0.530	**0.664**	0.208
	SD	3.110	3.640	1.776	2.001	2.966	2.188	2.372	3.333	3.145	5.072	5.344	2.118
	Obs	60	60	60	270	195	15	75	15	390	60	120	15
Non-event days	Mean	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	**0.000**	**-0.000**	0.000	**-0.000**	0.000
	Med	0.051	0.024	0.006	0.054	-0.058	-0.030	-0.013	**-0.239**	**-0.030**	-0.197	**-0.030**	0.048
	SD	2.276	1.921	1.566	1.747	2.689	2.396	1.584	6.739	2.244	2.582	2.037	3.548
	Obs	740	740	740	3330	2405	185	925	185	4810	740	1480	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.925	-0.309	1.003	0.504	-0.130	-0.407	-0.777	**2.224**^{b}	**-3.899**^{a}	-0.684	**-2.095**^{b}	-1.261
	TT p-val	0.359	0.758	0.319	0.615	0.897	0.689	0.440	0.036	0.000	0.497	0.038	0.221
meds	KW χ^2-stat	2.520	0.560	0.241	1.262	0.003	0.287	0.614	**3.859**^{b}	**12.976**^{a}	0.007	**16.172**^{a}	0.900
	KW p-val	0.112	0.454	0.623	0.261	0.959	0.592	0.433	0.049	0.000	0.934	0.000	0.343
vars	VR F-stat	**0.536**^{a}	**0.278**^{a}	0.777	**0.762**^{a}	**0.822**^{c}	1.199	**0.446**^{a}	**4.087**^{a}	**0.509**^{a}	**0.259**^{a}	**0.145**^{a}	**2.807**^{b}
	VR p-val	0.000	0.000	0.156	0.002	0.053	0.737	0.000	0.004	0.000	0.000	0.000	0.031

Table to be continued

Table C-2 – continued

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel B: December 22, 2011 (first three-year LTRO settlement)													
Event	Mean	**0.526**	0.289	0.295	-0.002	0.190	0.164	0.116	-0.259	0.215	0.683	0.027	1.445
days	Med	**0.241**	0.142	0.078	0.036	-0.023	-0.049	0.014	-0.812	0.012	**0.432**	-0.004	1.215
	SD	1.956	2.479	1.678	1.753	3.424	1.911	1.442	3.943	3.053	4.029	2.679	3.750
	Obs	60	60	60	270	195	15	75	15	390	60	120	15
Non-	Mean	**0.000**	0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000
event	Med	**0.039**	0.008	0.035	0.054	-0.066	-0.039	-0.037	-0.450	-0.034	**-0.226**	-0.064	0.039
days	SD	2.259	2.134	1.590	1.783	2.695	2.392	1.669	6.768	2.347	2.826	2.470	3.576
	Obs	740	740	740	3330	2405	185	925	185	4810	740	1480	185
Event vs non-event days: Test for equal													
means	TT t-stat	**-1.980**^{c}	-0.877	-1.317	0.019	-0.758	-0.313	-0.661	0.229	-1.361	-1.288	-0.107	-1.440
	TT p-val	0.052	0.383	0.192	0.985	0.449	0.758	0.510	0.821	0.174	0.202	0.915	0.169
meds	KW χ^2-stat	**3.174**^{c}	0.718	0.677	0.002	0.093	0.104	0.072	0.172	0.156	**3.106**^{c}	0.159	1.917
	KW p-val	0.075	0.397	0.411	0.965	0.761	0.747	0.789	0.678	0.693	0.078	0.690	0.166
vars	VR F-stat	1.335	**0.741**^{c}	0.898	1.034	**0.619**^{a}	1.567	1.340	**2.946**^{b}	**0.591**^{a}	**0.492**^{a}	0.850	0.909
	VR p-val	0.164	0.091	0.533	0.728	0.000	0.338	0.111	0.024	0.000	0.000	0.204	0.721
Panel C: March 1, 2012 (second three-year LTRO settlement)													
Event	Mean	-0.054	0.276	-0.005	**0.233**	0.165	-0.228	-0.189	-1.438	-0.012	**-0.548**	-0.411	-1.510
days	Med	0.051	0.142	-0.085	**0.145**	0.021	-0.130	-0.126	-2.559	0.027	-0.391	**-0.420**	**-3.403**
	SD	1.833	1.576	1.221	1.492	3.064	0.741	1.357	9.229	2.239	2.227	3.009	8.851
	Obs	60	60	60	270	195	15	75	15	390	60	120	15
Non-	Mean	-0.000	-0.000	0.000	**-0.000**	-0.000	0.000	0.000	-0.000	0.000	**0.000**	0.000	0.000
event	Med	0.081	-0.083	-0.057	**-0.021**	-0.104	-0.086	-0.045	-1.046	-0.093	-0.181	**-0.029**	**0.063**
days	SD	2.569	2.453	1.714	1.899	2.977	1.417	1.770	7.832	2.652	3.379	2.628	4.344
	Obs	740	740	740	3330	2405	185	925	185	4810	740	1480	185
Event vs non-event days: Test for equal													
means	TT t-stat	0.212	-1.239	0.031	**-2.416**^{b}	-0.725	1.049	1.131	0.587	0.098	**1.749**^{c}	1.453	0.654
	TT p-val	0.833	0.219	0.975	0.016	0.469	0.305	0.261	0.566	0.922	0.084	0.149	0.523
meds	KW χ^2-stat	0.270	2.589	0.032	**5.924**^{b}	0.300	0.344	0.289	0.797	0.299	1.840	**6.825**^{a}	**3.987**^{b}
	KW p-val	0.604	0.108	0.858	0.015	0.584	0.557	0.591	0.372	0.584	0.175	0.009	0.046
vars	VR F-stat	**1.964**^{a}	**2.423**^{a}	**1.973**^{a}	**1.620**^{a}	0.944	**3.661**^{a}	**1.703**^{a}	0.720	**1.404**^{a}	**2.302**^{a}	**0.763**^{b}	**0.241**^{a}
	VR p-val	0.002	0.000	0.002	0.000	0.562	0.008	0.004	0.324	0.000	0.000	0.033	0.000

Supplementary Table C-3

Cumulative Average Abnormal Returns on Bank Stocks by Country Assessed with Brown and Warner (1980)'s Test Statistic and Using "STOXX Europe 600" as Market Index. This table provides CAR_c for seven different windows and the three events, as indicated in the table, based on the bank stock sample. Numbers are given in decimals. In Panel A, $t = 0$ is the announcement of the three-year LTROs (December 8, 2011). In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). CAR_c is calculated as average of CAR_i across banks within a country. CAR_i for each bank is calculated as the sum of $AR_{i,t}$ over the respective time window. Abnormal returns are estimated with the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is, for each country, based on the STOXX Europe 600 index. Significance is evaluated using the test statistic proposed by Brown and Warner (1980), which is presented in brackets underneath the CAR_c. a, b, and c next to the CAR_c denote significance at the levels of 1%, 5%, and 10%, respectively.

	Non-peripheral countries							Peripheral countries				
	Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
# of banks	4	4	4	18	13	1	5	1	26	4	8	1
Panel A: December 8, 2011 (announcement of three-year LTROs)												
$[0, 1]$	-0.025	-0.005	0.001	-0.003	0.003	-0.005	-0.012	-0.064	0.001	0.048	-0.012	0.039
	(-1.30)	(-0.35)	(0.08)	(-0.28)	(0.21)	(-0.14)	(-1.01)	(-0.66)	(0.06)	(1.63)	(-0.72)	(0.76)
$[0, 3]$	**-0.072**[a]	-0.032	-0.018	-0.012	-0.001	0.012	**-0.028**[c]	-0.176	-0.014	-0.034	-0.030	0.035
	(-2.63)	(-1.52)	(-0.96)	(-0.83)	(-0.05)	(0.25)	(-1.71)	(-1.29)	(-0.66)	(-0.81)	(-1.27)	(0.49)
$[-1, 1]$	-0.009	-0.003	-0.014	-0.001	0.005	0.001	-0.009	-0.076	0.007	**0.067**[c]	-0.017	0.036
	(-0.37)	(-0.14)	(-0.84)	(-0.08)	(0.26)	(0.02)	(-0.61)	(-0.64)	(0.39)	(1.85)	(-0.80)	(0.59)
$[-1, 3]$	**-0.055**[c]	-0.029	-0.033	-0.010	0.001	0.018	-0.025	-0.188	-0.008	-0.015	-0.035	0.033
	(-1.81)	(-1.24)	(-1.55)	(-0.62)	(0.02)	(0.33)	(-1.37)	(-1.23)	(-0.33)	(-0.32)	(-1.30)	(0.41)
$[-3, 3]$	-0.028	-0.007	-0.025	0.005	0.008	0.020	0.001	-0.194	0.030	0.026	**0.080**[b]	0.081
	(-0.77)	(-0.24)	(-0.98)	(0.26)	(0.30)	(0.31)	(0.06)	(-1.08)	(1.09)	(0.48)	(2.52)	(0.86)
$[-5, 5]$	0.034	0.039	-0.017	0.001	0.034	0.028	0.033	-0.171	**0.064**[c]	0.087	**0.121**[a]	0.074
	(0.76)	(1.13)	(-0.54)	(0.05)	(0.99)	(0.34)	(1.24)	(-0.76)	(1.84)	(1.26)	(3.05)	(0.63)
$[-7, 7]$	0.057	0.022	-0.036	-0.009	0.004	0.036	0.032	-0.331	**0.095**[b]	0.068	**0.154**[a]	0.115
	(1.08)	(0.54)	(-0.96)	(-0.34)	(0.11)	(0.39)	(1.03)	(-1.26)	(2.36)	(0.84)	(3.32)	(0.83)

Table to be continued

Table C-3 – continued

	Non-peripheral countries							Peripheral countries				
	Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
# of banks	4	4	4	18	13	1	5	1	26	4	8	1
	(1.08)	(0.54)	(-0.96)	(-0.34)	(0.11)	(0.39)	(1.03)	(-1.26)	(2.36)	(0.84)	(3.32)	(0.83)
Panel B: December 22, 2011 (first three-year LTRO settlement)												
$[0, 1]$	0.008	-0.022	0.020	-0.007	-0.017	0.002	-0.004	-0.013	-0.002	0.032	-0.013	0.049
	(0.40)	(-1.30)	(1.44)	(-0.67)	(-1.20)	(0.07)	(-0.36)	(-0.13)	(-0.16)	(1.02)	(-0.66)	(0.96)
$[0, 3]$	0.022	-0.010	0.008	-0.001	-0.002	-0.002	0.001	0.086	-0.014	**0.122**^{a}	-0.022	**0.119**^{c}
	(0.78)	(-0.43)	(0.41)	(-0.07)	(-0.12)	(-0.03)	(0.06)	(0.63)	(-0.66)	(2.76)	(-0.81)	(1.66)
$[-1, 1]$	0.011	-0.025	0.014	0.002	-0.008	0.002	0.008	0.034	0.009	0.042	-0.016	**0.106**^{c}
	(0.46)	(-1.25)	(0.83)	(0.16)	(-0.45)	(0.04)	(0.53)	(0.29)	(0.50)	(1.10)	(-0.69)	(1.70)
$[-1, 3]$	0.025	-0.014	0.002	0.008	0.007	-0.002	0.013	0.133	-0.003	**0.132**^{a}	-0.026	**0.176**^{b}
	(0.80)	(-0.53)	(0.11)	(0.49)	(0.30)	(-0.04)	(0.69)	(0.87)	(-0.11)	(2.68)	(-0.84)	(2.19)
$[-3, 3]$	0.041	0.016	0.021	0.020	0.012	-0.033	0.021	0.045	0.015	**0.111**^{c}	0.029	**0.208**^{b}
	(1.08)	(0.53)	(0.81)	(0.99)	(0.44)	(-0.52)	(0.95)	(0.25)	(0.52)	(1.90)	(0.80)	(2.18)
$[-5, 5]$	0.072	**0.068**^{c}	0.018	0.016	0.006	0.008	0.020	0.037	0.036	**0.189**^{b}	0.017	**0.229**^{c}
	(1.53)	(1.74)	(0.55)	(0.65)	(0.18)	(0.10)	(0.70)	(0.16)	(1.00)	(2.58)	(0.37)	(1.91)
$[-7, 7]$	0.079	0.043	0.044	-0.000	0.029	0.025	0.017	-0.039	0.032	0.102	0.004	0.217
	(1.43)	(0.96)	(1.16)	(-0.01)	(0.73)	(0.26)	(0.53)	(-0.15)	(0.77)	(1.20)	(0.08)	(1.55)
Panel C: March 1, 2012 (second three-year LTRO settlement)												
$[0, 1]$	0.002	0.007	-0.006	0.002	0.011	0.000	0.005	-0.031	0.025	-0.007	0.020	**0.234**^{a}
	(0.09)	(0.38)	(-0.38)	(0.21)	(0.69)	(0.00)	(0.36)	(-0.27)	(1.43)	(-0.17)	(1.01)	(3.78)
$[0, 3]$	-0.005	0.001	-0.009	0.002	-0.012	-0.008	0.005	0.131	0.021	-0.013	0.011	**0.229**^{a}
	(-0.14)	(0.05)	(-0.43)	(0.09)	(-0.56)	(-0.27)	(0.28)	(0.83)	(0.87)	(-0.24)	(0.37)	(2.61)
$[-1, 1]$	0.017	0.011	0.006	0.008	0.022	-0.001	-0.010	0.067	0.033	-0.000	0.020	**0.295**^{a}
	(0.59)	(0.49)	(0.33)	(0.52)	(1.19)	(-0.06)	(-0.62)	(0.49)	(1.56)	(-0.00)	(0.81)	(3.88)
$[-1, 3]$	0.010	0.005	0.003	0.007	-0.001	-0.009	-0.010	0.229	0.030	-0.006	0.010	**0.289**^{a}
	(0.27)	(0.18)	(0.11)	(0.35)	(-0.03)	(-0.29)	(-0.46)	(1.29)	(1.08)	(-0.10)	(0.32)	(2.96)
$[-3, 3]$	0.008	0.016	-0.003	0.010	-0.003	-0.007	-0.007	0.148	0.016	0.013	-0.016	**0.213**^{c}
	(0.19)	(0.45)	(-0.09)	(0.43)	(-0.10)	(-0.19)	(-0.27)	(0.71)	(0.49)	(0.17)	(-0.43)	(1.84)
$[-5, 5]$	0.042	0.042	0.001	0.035	0.033	-0.002	-0.010	0.225	0.004	-0.020	-0.058	0.103
	(0.75)	(0.94)	(0.02)	(1.26)	(0.90)	(-0.04)	(-0.33)	(0.86)	(0.09)	(-0.22)	(-1.23)	(0.71)
$[-7, 7]$	-0.008	0.041	-0.001	0.035	0.025	-0.034	-0.028	-0.216	-0.002	-0.082	-0.062	-0.227
	(-0.13)	(0.79)	(-0.02)	(1.08)	(0.58)	(-0.62)	(-0.79)	(-0.71)	(-0.04)	(-0.77)	(-1.11)	(-1.34)

Supplementary Table C-4

Cumulative Average Abnormal Returns on Bank Stocks by Country Assessed with Kolari and Pynnönen (2010)'s Test Statistic and Using "STOXX Europe 600" as Market Index. This table provides CAR_c for seven different windows and the three events, as indicated in the table, based on the bank stock sample for sample countries with more than one bank. Numbers are given in decimals. In Panel A, $t = 0$ is the announcement of the three-year LTROs (December 8, 2011). In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). CAR_c is calculated as average of CAR_i across banks within a country. CAR_i for each bank is calculated as the sum of $AR_{i,t}$ over the respective time window. Abnormal returns are estimated with the market model in Eq. 3.2 using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is, for each country, based on the STOXX Europe 600 index. Significance is evaluated using both the test statistic proposed by Boehmer, Musumeci, and Poulsen (1991) presented in brackets underneath the CAR_c, which controls for event-induced changes in variance, and Kolari and Pynnönen (2010) presented in square brackets underneath Boehmer, Musumeci, and Poulsen (1991)'s test statistic, which controls for both event-induced changes in variance and cross-correlation. a, b, and c next to the CAR_c denote significance levels of 1%, 5%, and 10%, respectively, with the Boehmer, Musumeci, and Poulsen (1991) test statistic and, in square brackets, the Kolari and Pynnönen (2010) test statistic.

	Non-peripheral countries						Peripheral countries		
	Austria	Belgium	Finland	France	Germany	Netherl.	Italy	Portugal	Spain
# of banks	4	4	4	18	13	5	26	4	8
Panel A: December 8, 2011 (announcement of three-year LTROs)									
$[0,1]$	-0.025	-0.005	0.001	-0.003	0.003	-0.012	0.001	0.048	-0.012
	(-1.44)	(-1.43)	(-0.02)	(-0.78)	(0.56)	(-0.93)	(-0.34)	(1.05)	(0.27)
	[-0.89]	[-1.00]	[-0.01]	[-0.41]	[0.36]	[-0.74]	[-0.13]	[0.41]	[0.10]
$[0,3]$	**-0.072**$^{b,[\cdot]}$	**-0.032**$^{a,[a]}$	-0.018	-0.012	-0.001	-0.028	-0.014	-0.034	-0.030
	(-2.13)	(-4.63)	(-1.33)	(-1.03)	(0.49)	(-1.61)	(-0.90)	(0.06)	(-0.40)
	[-1.32]	[-3.25]	[-0.82]	[-0.54]	[0.31]	[-1.29]	[-0.35]	[0.02]	[-0.15]
$[-1,1]$	-0.009	-0.003	-0.014	-0.001	0.005	-0.009	0.007	0.067	-0.017
	(1.00)	(-0.35)	(-0.88)	(0.23)	(1.00)	(-0.06)	(0.69)	(1.05)	(0.04)
	[0.62]	[-0.24]	[-0.54]	[0.12]	[0.64]	[-0.05]	[0.27]	[0.41]	[0.01]
$[-1,3]$	**-0.055**$^{a,[\cdot]}$	-0.029	-0.033	-0.010	0.001	-0.025	-0.008	-0.015	-0.035
	(-2.64)	(-1.22)	(-1.38)	(-0.39)	(0.81)	(-0.50)	(0.14)	(0.32)	(-0.56)
	[-1.64]	[-0.85]	[-0.86]	[-0.20]	[0.52]	[-0.40]	[0.05]	[0.13]	[-0.21]
$[-3,3]$	-0.028	-0.007	-0.025	**0.005**$^{a,[\cdot]}$	0.008	**0.001**$^{c,[\cdot]}$	**0.030**$^{a,[\cdot]}$	0.026	**0.080**$^{b,[\cdot]}$
	(-0.09)	(0.17)	(-1.49)	(2.92)	(1.11)	(1.83)	(2.93)	(0.71)	(2.07)
	[-0.06]	[0.12]	[-0.93]	[1.51]	[0.72]	[1.47]	[1.13]	[0.28]	[0.78]
$[-5,5]$	0.034	0.039	-0.017	0.001	**0.034**$^{a,[c]}$	**0.033**$^{a,[b]}$	**0.064**$^{a,[\cdot]}$	**0.087**$^{c,[\cdot]}$	**0.121**$^{a,[\cdot]}$
	(1.47)	(0.59)	(-0.48)	(0.44)	(2.61)	(3.04)	(3.30)	(1.69)	(3.57)
	[0.91]	[0.41]	[-0.30]	[0.23]	[1.67]	[2.44]	[1.27]	[0.66]	[1.35]
$[-7,7]$	0.057	0.022	**-0.036**$^{a,[c]}$	**-0.009**$^{b,[\cdot]}$	0.004	**0.032**$^{c,[\cdot]}$	**0.095**$^{b,[\cdot]}$	0.068	**0.154**$^{a,[\cdot]}$
	(1.50)	(-0.26)	(-2.67)	(-2.51)	(0.32)	(1.81)	(2.57)	(0.91)	(2.67)
	[0.93]	[-0.18]	[-1.65]	[-1.30]	[0.20]	[1.45]	[0.99]	[0.36]	[1.02]

Table to be continued

Table C-4 – continued

	Non-peripheral countries						Peripheral countries		
	Austria	Belgium	Finland	France	Germany	Netherl.	Italy	Portugal	Spain
# of banks	4	4	4	18	13	5	26	4	8
Panel B: December 22, 2011 (first three-year LTRO cash settlement)									
$[0, 1]$	0.008	-0.022	0.020	-0.007	**-0.017**$^{a,[c]}$	-0.004	-0.002	0.032	-0.013
	(0.58)	(-1.03)	(0.86)	(-0.65)	(-2.70)	(-0.53)	(-0.05)	(0.90)	(-1.65)
	[0.36]	[-0.72]	[0.49]	[-0.33]	[-1.84]	[-0.37]	[-0.02]	[0.36]	[-0.63]
$[0, 3]$	0.022	-0.010	0.008	-0.001	-0.002	0.001	-0.014	**0.122**$^{c,[\cdot]}$	**-0.022**$^{b,[\cdot]}$
	(1.07)	(-0.42)	(0.77)	(-0.03)	(-1.24)	(0.02)	(-1.30)	(1.86)	(-2.08)
	[0.66]	[-0.30]	[0.44]	[-0.01]	[-0.85]	[0.02]	[-0.50]	[0.74]	[-0.79]
$[-1, 1]$	0.011	**-0.025**$^{c,[\cdot]}$	0.014	0.002	-0.008	**0.008**$^{c,[\cdot]}$	0.009	0.042	**-0.016**$^{c,[\cdot]}$
	(0.43)	(-1.94)	(0.53)	(1.28)	(-0.26)	(1.80)	(0.77)	(0.99)	(-1.77)
	[0.26]	[-1.35]	[0.30]	[0.66]	[-0.18]	[1.26]	[0.29]	[0.40]	[-0.67]
$[-1, 3]$	0.025	-0.014	0.002	**0.008**$^{c,[\cdot]}$	0.007	**0.013**$^{a,[b]}$	-0.003	**0.132**$^{c,[\cdot]}$	**-0.026**$^{b,[\cdot]}$
	(0.81)	(-0.97)	(0.23)	(1.83)	(0.24)	(2.84)	(0.26)	(1.83)	(-2.11)
	[0.50]	[-0.68]	[0.13]	[0.94]	[0.16]	[1.99]	[0.10]	[0.73]	[-0.80]
$[-3, 3]$	**0.041**$^{b,[\cdot]}$	**0.016**$^{c,[\cdot]}$	0.021	**0.020**$^{b,[\cdot]}$	0.012	0.021	0.015	0.111	**0.029**$^{a,[\cdot]}$
	(2.32)	(1.78)	(1.45)	(2.10)	(0.92)	(0.88)	(1.30)	(1.32)	(2.67)
	[1.43]	[1.24]	[0.83]	[1.08]	[0.62]	[0.62]	[0.50]	[0.53]	[1.01]
$[-5, 5]$	**0.072**$^{b,[\cdot]}$	0.068	**0.018**$^{b,[\cdot]}$	0.016	0.006	0.020	0.036	**0.189**$^{a,[c]}$	**0.017**$^{b,[\cdot]}$
	(2.47)	(1.53)	(2.24)	(0.80)	(1.03)	(1.16)	(1.53)	(4.37)	(2.50)
	[1.52]	[1.07]	[1.27]	[0.41]	[0.70]	[0.82]	[0.59]	[1.74]	[0.95]
$[-7, 7]$	**0.079**$^{a,[c]}$	0.043	0.044	-0.000	0.029	0.017	0.032	0.102	0.004
	(3.11)	(0.12)	(1.35)	(-0.86)	(1.31)	(1.21)	(0.64)	(-0.79)	(0.57)
	[1.91]	[0.08]	[0.77]	[-0.44]	[0.89]	[0.85]	[0.24]	[-0.31]	[0.21]

Table to be continued

Table C-4 – continued

	Non-peripheral countries						Peripheral countries		
	Austria	Belgium	Finland	France	Germany	Netherl.	Italy	Portugal	Spain
# of banks	4	4	4	18	13	5	26	4	8
Panel C: March 1, 2012 (second three-year LTRO cash settlement)									
$[0, 1]$	0.002	**0.007**$^{c,[\cdot]}$	-0.006	0.002	0.011	0.005	**0.025**$^{a,[\cdot]}$	-0.007	0.020
	(0.52)	(1.92)	(-0.55)	(-0.09)	(0.71)	(0.50)	(4.28)	(-0.51)	(0.31)
	[0.39]	[1.47]	[-0.37]	[-0.04]	[0.47]	[0.41]	[1.65]	[-0.20]	[0.12]
$[0, 3]$	-0.005	0.001	-0.009	0.002	-0.012	0.005	**0.021**$^{a,[\cdot]}$	-0.013	0.011
	(0.40)	(1.36)	(-0.59)	(0.08)	(-0.99)	(0.88)	(3.32)	(-0.78)	(-0.60)
	[0.29]	[1.05]	[-0.40]	[0.04]	[-0.66]	[0.72]	[1.27]	[-0.31]	[-0.23]
$[-1, 1]$	0.017	0.011	0.006	**0.008**$^{c,[\cdot]}$	**0.022**$^{b,[\cdot]}$	**-0.010**$^{c,[\cdot]}$	**0.033**$^{a,[c]}$	-0.000	0.020
	(1.20)	(1.30)	(0.87)	(1.75)	(2.00)	(-1.83)	(4.34)	(0.44)	(0.32)
	[0.88]	[1.00]	[0.59]	[0.81]	[1.33]	[-1.49]	[1.67]	[0.17]	[0.12]
$[-1, 3]$	0.010	0.005	0.003	0.007	-0.001	-0.010	**0.030**$^{a,[\cdot]}$	-0.006	0.010
	(1.41)	(0.85)	(0.63)	(1.60)	(0.82)	(-1.24)	(3.55)	(-0.10)	(-0.54)
	[1.04]	[0.65]	[0.43]	[0.74]	[0.54]	[-1.01]	[1.36]	[-0.04]	[-0.21]
$[-3, 3]$	**0.008**$^{c,[\cdot]}$	0.016	-0.003	**0.010**$^{b,[\cdot]}$	-0.003	-0.007	0.016	0.013	**-0.016**$^{c,[\cdot]}$
	(1.81)	(1.57)	(-0.86)	(1.98)	(0.55)	(-0.92)	(-0.02)	(0.34)	(-1.87)
	[1.33]	[1.20]	[-0.59]	[0.91]	[0.36]	[-0.75]	[-0.01]	[0.14]	[-0.72]
$[-5, 5]$	**0.042**$^{a,[a]}$	**0.042**$^{a,[b]}$	**0.001**$^{a,[a]}$	**0.035**$^{a,[\cdot]}$	0.033	-0.010	**0.004**$^{c,[\cdot]}$	**-0.020**$^{b,[\cdot]}$	**-0.058**$^{a,[\cdot]}$
	(3.73)	(3.20)	(6.16)	(3.18)	(1.42)	(-0.51)	(-1.80)	(-2.10)	(-4.06)
	[2.75]	[2.45]	[4.19]	[1.47]	[0.94]	[-0.41]	[-0.69]	[-0.83]	[-1.56]
$[-7, 7]$	-0.008	**0.041**$^{a,[b]}$	-0.001	**0.035**$^{a,[\cdot]}$	0.025	-0.028	-0.002	**-0.082**$^{a,[c]}$	**-0.062**$^{a,[\cdot]}$
	(-0.49)	(2.73)	(1.33)	(3.52)	(0.21)	(-0.71)	(0.47)	(-4.36)	(-2.66)
	[-0.36]	[2.10]	[0.90]	[1.63]	[0.14]	[-0.57]	[0.18]	[-1.73]	[-1.02]

Supplementary Table C-5

Comparison of Abnormal Returns on Bank Indices on Event versus Non-Event Days per Country. This table compares estimated abnormal returns on event to those on non-event days for the bank index return sample by country. Numbers are in percentage points. Countries are classified into non-peripheral and peripheral countries as indicated in the table. Each of the three panels provides sample means, medians, standard deviations, and number of observations on event days and non-event days. In each panel and for each country the table shows two-sample t-tests for equal means, Kruskal-Wallis χ^2-tests for equal medians, and variance-ratio F-tests for equal variances comparing event and non-event day abnormal returns. Abnormal returns are estimated with the market model in Eq. 3.2 (by replacing subscript i by subscript c) using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is based on a country-level total market return index (see Section 3.3). For each country in each panel the tests are based on a total of $[-192, 7] = 200$ days: $[-7, 7] = 15$ event days and $[-192, -8] = 185$ non-event days. In Panel A, $t = 0$ is the announcement of the three-year LTROs on December 8, 2011. In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). Test statistics and corresponding means, medians, and/or variances that are significant at the level of at least 10% are marked in bold. a, b, and c next to the test statistics denote significance at the levels of 1%, 5%, and 10%, respectively.

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel A: December 8, 2011 (announcement of three-year LTROs)													
Event	Mean	0.323	0.864	0.515	0.130	0.386	-0.002	**-0.651**	**-1.818**	0.402	-0.496	0.241	-0.159
days	Med	0.263	1.338	**0.525**	-0.428	-0.007	0.020	**-0.879**	**-0.815**	0.264	-0.135	0.158	0.082
	SD	2.191	5.352	1.222	2.381	1.702	0.195	1.380	2.802	0.961	3.392	0.777	2.258
	Obs	15	15	15	15	15	15	15	15	15	15	15	15
Non-	Mean	-0.000	0.000	0.000	-0.000	-0.000	-0.000	**-0.000**	**0.000**	-0.000	-0.000	-0.000	0.000
event	Med	0.096	0.018	**-0.043**	-0.096	-0.142	0.006	**0.064**	**0.006**	-0.067	-0.014	-0.060	0.003
days	SD	1.448	2.315	1.087	2.043	1.704	0.258	1.467	2.889	1.308	2.231	0.637	1.918
	Obs	185	185	185	185	185	185	185	185	185	185	185	185
Event vs non-event days:	*Test for equal*												
means	TT t-stat	-0.561	-0.621	-1.583	-0.206	-0.844	0.032	**1.749**^{c}	**2.412**^{b}	-1.511	0.556	-1.167	0.264
	TT p-val	0.583	0.544	0.133	0.839	0.411	0.975	0.099	0.028	0.148	0.586	0.261	0.795
meds	KW χ^2-stat	0.678	0.292	**3.331**^{c}	0.272	0.773	0.002	**4.562**^{b}	**5.325**^{b}	1.741	0.258	1.982	0.016
	KW p-val	0.410	0.589	0.068	0.602	0.379	0.968	0.033	0.021	0.187	0.612	0.159	0.899
vars	VR F-stat	**0.437**^{b}	**0.187**^{a}	0.791	0.737	1.003	1.762	1.130	1.063	1.851	**0.433**^{b}	0.672	0.721
	VR p-val	0.013	0.000	0.467	0.356	0.916	0.224	0.848	0.967	0.187	0.012	0.238	0.327

Table to be continued

Table C-5 – continued

		Non-peripheral countries							Peripheral countries				
		Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
Panel B: December 22, 2011 (first three-year LTRO settlement)													
Event	Mean	0.265	-0.399	0.164	-0.473	0.157	0.055	0.553	-0.349	-0.143	1.271	0.068	0.813
days	Med	0.451	-0.027	0.134	-0.720	0.106	0.006	0.114	0.179	-0.128	**1.508**	0.018	0.925
	SD	1.433	1.954	0.652	1.147	0.924	0.360	2.066	1.970	1.244	3.318	0.503	2.713
	Obs	15	15	15	15	15	15	15	15	15	15	15	15
Non-	Mean	0.000	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
event	Med	0.084	-0.012	-0.069	-0.143	-0.183	0.014	0.043	0.063	-0.063	**0.004**	-0.013	-0.058
days	SD	1.499	2.709	1.088	2.111	1.739	0.254	1.400	2.964	1.319	2.349	0.650	1.981
	Obs	185	185	185	185	185	185	185	185	185	185	185	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.687	0.735	-0.879	1.415	-0.581	-0.581	-1.018	0.630	0.425	-1.454	-0.489	-1.136
	TT p-val	0.501	0.471	0.389	0.171	0.567	0.570	0.325	0.536	0.676	0.166	0.631	0.274
meds	KW χ^2-stat	0.981	0.372	1.494	1.276	0.701	0.027	0.685	0.184	0.244	**5.092**^{b}	0.230	1.956
	KW p-val	0.322	0.542	0.222	0.259	0.402	0.869	0.408	0.668	0.621	0.024	0.631	0.162
vars	VR F-stat	1.094	1.922	**2.784**^{b}	**3.386**^{b}	**3.543**^{a}	**0.500**^{b}	**0.459**^{b}	**2.264**^{c}	1.126	**0.501**^{b}	1.667	**0.533**^{c}
	VR p-val	0.910	0.161	0.032	0.012	0.010	0.040	0.020	0.082	0.855	0.040	0.274	0.063
Panel C: March 1, 2012 (second three-year LTRO settlement)													
Event	Mean	0.087	0.225	-0.065	-0.084	0.083	0.068	-0.253	-0.275	-0.266	-0.798	-0.034	-0.253
days	Med	-0.109	0.534	0.029	-0.274	0.047	0.036	0.196	-0.252	-0.052	-0.650	-0.057	-0.952
	SD	1.455	1.984	0.739	1.141	1.090	0.516	1.937	2.477	0.903	2.111	0.441	3.317
	Obs	15	15	15	15	15	15	15	15	15	15	15	15
Non-	Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000
event	Med	0.048	-0.126	-0.040	-0.147	-0.126	0.002	-0.008	0.158	-0.017	-0.044	-0.033	0.058
days	SD	1.732	3.103	1.051	2.235	1.923	0.261	1.594	3.293	1.575	2.881	0.692	2.426
	Obs	185	185	185	185	185	185	185	185	185	185	185	185
Event vs non-event days: Test for equal													
means	TT t-stat	-0.218	-0.400	0.317	0.249	-0.264	-0.507	0.492	0.403	1.020	1.365	0.274	0.290
	TT p-val	0.830	0.693	0.755	0.805	0.794	0.620	0.629	0.692	0.319	0.189	0.787	0.776
meds	KW χ^2-stat	0.001	0.244	0.071	0.006	0.333	0.098	0.157	0.378	0.455	1.816	0.007	0.865
	KW p-val	0.972	0.621	0.790	0.939	0.564	0.754	0.692	0.539	0.500	0.178	0.932	0.352
vars	VR F-stat	1.418	**2.446**^{c}	2.022	**3.841**^{a}	**3.114**^{b}	**0.256**^{a}	0.677	1.767	**3.044**^{b}	1.863	**2.458**^{c}	**0.535**^{c}
	VR p-val	0.465	0.058	0.132	0.006	0.018	0.000	0.246	0.222	0.021	0.182	0.057	0.065

Supplementary Table C-6

Cumulative Average Abnormal Returns on Bank Indices by Country Assessed with Brown and Warner (1980)'s Test Statistic. This table provides CAR_c for seven different windows and the three events, as indicated in the table, based on country-level bank indices. Numbers are given in decimals. In Panel A, $t = 0$ is the announcement of the three-year LTROs (December 8, 2011). In Panel B (C), $t = 0$ represents the first (second) three-year LTRO cash settlement on December 22, 2011 (March 1, 2012). CAR_c for each bank index is calculated as the sum of $AR_{c,t}$ over the respective time window. Abnormal returns are estimated with the market model in Eq. 3.2 (by replacing subscript i by subscript c) using the estimation window $[T_0, T_1] = [-192, -8]$ for each event (panel) separately. $r_{m,t}$ is based on a country-level total market return index (see Section 3.3). Significance is evaluated using the test statistic proposed by Brown and Warner (1980) which is presented in brackets underneath the CAR_c. a, b, and c next to the CAR_c denote significance at the levels of 1%, 5%, and 10%, respectively.

	Non-peripheral countries							Peripheral countries				
	Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
# of indices	1	1	1	1	1	1	1	1	1	1	1	1
Panel A: December 8, 2011 (announcement of three-year LTROs)												
$[0, 1]$	**-0.036**^{c}	-0.003	0.004	-0.009	-0.002	0.001	0.004	-0.002	-0.003	-0.008	0.000	0.033
	(-1.75)	(-0.08)	(0.26)	(-0.30)	(-0.08)	(0.19)	(0.19)	(-0.05)	(-0.15)	(-0.27)	(0.04)	(1.21)
$[0, 3]$	**-0.082**^{a}	-0.045	-0.003	-0.034	-0.017	-0.002	0.015	-0.089	-0.013	-0.059	-0.007	0.035
	(-2.82)	(-0.97)	(-0.16)	(-0.83)	(-0.49)	(-0.46)	(0.51)	(-1.53)	(-0.51)	(-1.32)	(-0.57)	(0.90)
$[-1, 1]$	-0.023	0.048	-0.010	-0.012	0.007	0.001	0.013	-0.032	-0.003	-0.022	0.002	0.018
	(-0.92)	(1.18)	(-0.51)	(-0.34)	(0.23)	(0.30)	(0.51)	(-0.63)	(-0.14)	(-0.56)	(0.17)	(0.53)
$[-1, 3]$	**-0.069**^{b}	0.005	-0.017	-0.037	-0.008	-0.002	0.024	**-0.119**^{c}	-0.014	-0.073	-0.006	0.019
	(-2.12)	(0.09)	(-0.70)	(-0.81)	(-0.21)	(-0.30)	(0.73)	(-1.83)	(-0.47)	(-1.44)	(-0.40)	(0.45)
$[-3, 3]$	-0.037	0.071	0.007	0.006	-0.015	-0.003	0.018	-0.124	-0.001	-0.070	0.009	0.028
	(-0.97)	(1.16)	(0.25)	(0.11)	(-0.33)	(-0.49)	(0.47)	(-1.61)	(-0.03)	(-1.18)	(0.54)	(0.56)
$[-5, 5]$	0.025	**0.238**^{a}	0.046	0.035	0.074	-0.004	-0.042	**-0.203**^{b}	0.060	-0.040	**0.036**^{c}	0.059
	(0.52)	(3.07)	(1.26)	(0.52)	(1.30)	(-0.41)	(-0.85)	(-2.10)	(1.37)	(-0.54)	(1.70)	(0.91)
$[-7, 7]$	0.048	0.130	**0.077**^{c}	0.020	0.058	-0.000	**-0.098**^{c}	**-0.273**^{b}	0.060	-0.074	0.036	-0.024
	(0.86)	(1.43)	(1.82)	(0.25)	(0.87)	(-0.03)	(-1.70)	(-2.42)	(1.18)	(-0.85)	(1.45)	(-0.32)

Table to be continued

Table C-6 – continued

	Non-peripheral countries							Peripheral countries				
	Austria	Belgium	Finland	France	Germany	Malta	Netherl.	Greece	Italy	Portugal	Spain	Cyprus
# of indices	1	1	1	1	1	1	1	1	1	1	1	1
Panel B: December 22, 2011 (first three-year LTRO cash settlement)												
$[0,1]$	0.019	-0.045	0.004	-0.006	0.023	-0.002	**0.046**^{b}	0.007	-0.021	**0.065**^{c}	-0.005	0.035
	(0.90)	(-1.15)	(0.29)	(-0.21)	(0.91)	(-0.60)	(2.29)	(0.18)	(-1.11)	(1.95)	(-0.51)	(1.22)
$[0,3]$	0.031	-0.039	-0.001	-0.020	0.018	-0.008	**0.093**^{a}	0.024	-0.035	**0.165**^{a}	-0.005	0.054
	(1.02)	(-0.72)	(-0.06)	(-0.47)	(0.52)	(-1.52)	(3.29)	(0.40)	(-1.33)	(3.47)	(-0.36)	(1.35)
$[-1,1]$	0.030	-0.050	0.007	-0.020	0.030	0.006	**0.049**^{b}	0.013	-0.023	**0.087**^{b}	-0.004	**0.072**^{b}
	(1.14)	(-1.05)	(0.38)	(-0.54)	(0.98)	(1.36)	(2.01)	(0.26)	(-0.99)	(2.13)	(-0.31)	(2.08)
$[-1,3]$	0.041	-0.044	0.001	-0.033	0.026	0.000	**0.096**^{a}	0.030	-0.037	**0.187**^{a}	-0.004	**0.091**^{b}
	(1.23)	(-0.72)	(0.06)	(-0.70)	(0.66)	(0.08)	(3.05)	(0.45)	(-1.25)	(3.52)	(-0.24)	(2.05)
$[-3,3]$	0.034	-0.043	0.025	-0.018	0.031	0.002	0.055	0.007	-0.014	**0.183**^{a}	0.003	**0.109**^{b}
	(0.84)	(-0.59)	(0.87)	(-0.31)	(0.68)	(0.35)	(1.46)	(0.09)	(-0.41)	(2.93)	(0.17)	(2.06)
$[-5,5]$	0.071	-0.027	0.014	-0.021	0.035	0.005	**0.085**^{c}	0.040	-0.008	**0.259**^{a}	0.021	**0.133**^{b}
	(1.41)	(-0.29)	(0.38)	(-0.30)	(0.60)	(0.63)	(1.82)	(0.40)	(-0.18)	(3.30)	(0.96)	(2.01)
$[-7,7]$	0.040	-0.060	0.025	-0.071	0.024	0.008	0.083	-0.052	-0.021	**0.191**^{b}	0.010	0.122
	(0.68)	(-0.57)	(0.58)	(-0.86)	(0.35)	(0.83)	(1.52)	(-0.45)	(-0.42)	(2.08)	(0.40)	(1.58)
Panel C: March 1, 2012 (second three-year LTRO cash settlement)												
$[0,1]$	0.010	0.024	0.010	0.010	0.012	0.002	-0.023	0.005	0.001	-0.029	0.000	**0.077**^{b}
	(0.40)	(0.54)	(0.65)	(0.31)	(0.45)	(0.58)	(-1.03)	(0.11)	(0.03)	(-0.71)	(0.04)	(2.24)
$[0,3]$	0.007	0.019	-0.004	0.004	0.003	**0.009**^{c}	-0.029	0.048	0.001	-0.025	-0.007	**0.105**^{b}
	(0.20)	(0.30)	(-0.21)	(0.10)	(0.09)	(1.73)	(-0.89)	(0.72)	(0.02)	(-0.44)	(-0.50)	(2.14)
$[-1,1]$	0.048	0.032	0.012	0.015	0.022	0.003	-0.021	0.006	0.008	-0.021	0.006	**0.084**^{b}
	(1.59)	(0.60)	(0.67)	(0.39)	(0.66)	(0.60)	(-0.77)	(0.10)	(0.28)	(-0.41)	(0.48)	(1.97)
$[-1,3]$	0.045	0.027	-0.002	0.010	0.013	0.010	-0.027	0.048	0.008	-0.017	-0.002	**0.111**^{b}
	(1.16)	(0.39)	(-0.08)	(0.19)	(0.31)	(1.65)	(-0.74)	(0.65)	(0.22)	(-0.26)	(-0.11)	(2.03)
$[-3,3]$	0.042	0.038	0.018	0.008	0.007	0.008	-0.009	0.032	0.004	0.004	-0.007	0.085
	(0.90)	(0.45)	(0.62)	(0.13)	(0.13)	(1.17)	(-0.21)	(0.36)	(0.09)	(0.06)	(-0.35)	(1.31)
$[-5,5]$	0.065	0.084	0.012	0.023	0.050	0.002	-0.030	0.047	0.001	-0.050	0.006	0.070
	(1.13)	(0.81)	(0.33)	(0.31)	(0.77)	(0.26)	(-0.57)	(0.43)	(0.03)	(-0.52)	(0.26)	(0.86)
$[-7,7]$	0.013	0.034	-0.010	-0.013	0.012	0.010	-0.038	-0.041	-0.040	-0.120	-0.005	-0.038
	(0.19)	(0.28)	(-0.24)	(-0.14)	(0.17)	(1.00)	(-0.61)	(-0.32)	(-0.65)	(-1.06)	(-0.19)	(-0.40)

Part IV

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Part V

Curriculum Vitae

Curriculum Vitae

Personal details

Name:	René Hegglin
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Education

09/2011 – 10/2017	**PhD program at the Department of Banking and Finance** University of Zurich (Switzerland) Supervisor: Prof. Dr. Urs W. Birchler
09/2008 – 10/2011	**Master of Arts in Banking and Finance** University of Zurich (Switzerland) 09/2009 – 12/2009: Exchange at Fisher College of Business Ohio State University (Columbus, United States)
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Professional experience

Since 09/2015	**Managing Director, Head of Administration** Department of Banking and Finance, University of Zurich
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